

IMITATION LEARNING THROUGH SELF-EXPLORATION:
FROM BODY-BABBLING TO VISUOMOTOR ASSOCIATION

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ASSOCIATION

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ABSTRACT

Mirror neurons are visuo-motor neurons found in primates and thought to be significant for imitation learning. The proposition that mirror neurons result from associative learning while the neonate observes his own actions has received noteworthy empirical support. Imitation learning through self-exploration is essential in development of sensorimotor skills in infants. Self-exploration is regarded as a procedure by which infants become perceptually observant to their own body and engage in a perceptual communication with themselves. It is assumed that crude sense of self is the prerequisite for social interaction rather than an outcome of it. However, role of mirror neuron in encoding the perspective from which the motor acts of others are seen have not been addressed in relation to humanoid robots. In this thesis, I present a computational model for development of mirror neuron system based on the hypothesis that infants acquire mirror neuron system by sensorimotor associative learning through self-exploration empowering it to understand the perceived action by taking into account the view-dependency of neurons as a probable outcome of their associative connectivity.

In our mirror experiment, a humanoid robot stands in front of a glass mirror in order to obtain the associative relationship between his own motor generated actions and his own visual body-image. First, the continuous flow of motion patterns is segmented into motion primitives by identifying the boundaries of actions through Incremental Kernel Slow Feature Analysis. The segmentation model directly operates on the images acquired from the robot's vision sensor (camera) without requiring any kinematic model of the demonstrator. After segmentation, the spatio-temporal motion sequences are learned incrementally through Topological Gaussian Adaptive Resonance Hidden Markov Model. Later, a visuo-motor association is developed through novel Topological Gaussian Adaptive Resonance Associative Memory. The learning model dynamically generates the topo-

logical structure in a self-stabilizing manner. Finally, after learning, the robot partner performs a similar action in front of the robot and the robot recalls the corresponding motor command from the memory. In the learning process the network first forms mapping from each motor representation onto visual representation from the self-exploratory perspective. Afterwards, the representation of the motor commands is learned to be associated with all possible visual perspectives. The complete architecture was evaluated by simulation experiments performed on DARwIn-OP humanoid robot. The results show that the imitation learning algorithm is able to incrementally learn and associate the observed motion patterns based on the segmentation of motion primitives.

ABSTRAK

Neuron cermin adalah neuron visuo-motor yang terdapat dalam primat dan dianggap penting untuk pembelajaran tiruan. Usul bahawa neuron cermin hasil dari pembelajaran bersekutu manakala neonate memerhati tindakannya sendiri telah menerima sokongan empirikal perlu diberi perhatian. Pembelajaran tiruan melalui penerokaan diri adalah penting di dalam pembangunan kemahiran sensorimotor pada bayi. Self-penerokaan dianggap sebagai suatu tatacara yang bayi menjadi perceptually taat kepada badan mereka sendiri dan melibatkan diri dalam komunikasi persepsi dengan diri mereka sendiri. Ia menganggap bahawa rasa mentah diri adalah prasyarat untuk interaksi sosial dan bukannya hasil daripada ia. Walau bagaimanapun, peranan cermin neuron dalam pengekodan perspektif yang motor perbuatan orang lain dilihat tidak ditangani berhubung dengan robot humanoid. Dalam tesis ini, saya membentangkan model pengkomputeran untuk pembangunan sistem cermin neuron berdasarkan hipotesis bahawa bayi menggunakan sistem neuron cermin oleh sensorimotor bersekutu pembelajaran melalui penerokaan sendiri memberi kuasa kepada memahami tindakan yang dilihat dengan mengambil kira pandangan-pergantungan neuron sebagai hasil yang berkemungkinan sambungan bersekutu mereka.

Dalam eksperimen cermin kita, robot humanoid berdiri di hadapan sebuah cermin kaca untuk mendapatkan hubungan bersekutu antara tindakan motor yang dihasilkan sendiri dan visual badan-imej sendiri. Pertama, aliran berterusan corak gerakan dibahagikan kepada primitif gerakan dengan mengenal pasti sempadan tindakan melalui Peningkatan Kernel Analisis Ciri perlahan. Model segmentasi terus beroperasi pada imej-imej yang diperoleh daripada robot visi sensor (kamera) tanpa memerlukan apa-apa model kinematik demonstrasi itu. Selepas segmentasi, urutan gerakan spatio-temporal dipelajari secara berperingkat melalui Topological Gaussian Adaptive Resonance Hidden Markov

Model. Kemudian, sebuah persatuan visuo-motor dibangun melalui novel Topological Gaussian Adaptive Resonance Associative Memory bersekelu. Model pembelajaran dinamik menjana struktur topologi dengan cara sendiri stabil. Akhirnya, selepas pembelajaran, rakan robot yang melakukan tindakan yang sama di hadapan robot dan robot mengimbas kembali perintah motor yang sepadan dari memori. Dalam proses pembelajaran rangkaian pertama membentuk pemetaan dari setiap perwakilan motor ke perwakilan visual dari perspektif diri penerokaan itu. Selepas itu, perwakilan perintah motor belajar untuk dikaitkan dengan semua perspektif visual mungkin. Seni bina lengkap dinilai oleh eksperimen simulasi yang dilakukan ke atas Darwin-OP robot humanoid. Keputusan menunjukkan bahawa algoritma pembelajaran tiruan mampu secara berperingkat belajar dan mengaitkan corak gerakan diperhatikan berdasarkan pembahagian primitif gerakan.

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LIST OF SYMBOLS AND ACRONYMS

A	State transition probability matrix of HMM.
B	Observation probability distribution of HMM.
O_t	Observation sequence for TGAR-HMM.
V_t	Vision observation vector - visual features.
Γ_j	Covariance Matrix - TGARM node weight parameter.
$\bar{\Phi}_A$	Centered data matrix of Φ_A .
$\bar{\Phi}_B$	Centered data matrix of Φ_B .
\bar{X}_C	Centered data matrix of X_C .
\bar{Z}	Centred data matrix.
K	Kernel matrix.
Φ_A	Function to transform data matrix X_A to higher-dimensional space.
Φ_B	Function to transform new data matrix X_B to higher-dimensional space.
$\dot{\Phi}_A$	Temporal derivation matrix of Φ_A .
$\dot{\Phi}_B$	Temporal derivation matrix of Φ_B .
\dot{Z}	Temporal derivation matrix of Z .
μ_A	Mean of Φ_A .
μ_B	Mean of Φ_B .
μ_C	Mean of concatenated data matrix X_C .
μ_Z	Mean of data pattern Z .
δ	Change detected in data after time t .
$\dot{\bar{K}}$	Derivative of the centered kernel matrix \bar{K} .
\dot{y}	Derivative of y .
$\kappa(\cdot, \cdot)$	Kernel function.
$\langle y \rangle_t$	Temporal averaging of y .
v_t	Class label for visual feature vector.
π	State prior probabilities of HMM.
ρ	Vigilance parameter.
σ	Covariance matrix for state in HMM.
S	Whitening matrix to fulfil the unit variance constraint.
X_C	Overall data matrix represented by the concatenation of Φ_A and Φ_B .

\mathbf{Z}	Matrix containing input features such that $\mathbf{Z} = [\mathbf{z}_1, \dots, \mathbf{z}_n]$.
$\mathbf{g}(x)$	Function that transform $\mathbf{x}(t)$ into slowly-varying output signals, $\mathbf{y}(t)$.
$\mathbf{x}(t)$	Input Data for SFA.
$\mathbf{y}(t)$	Output Data for SFA.
$\mathbf{z}(t)$	Non-linearly expanded signal.
ξ_j	Mean value - TGARM node weight parameter.
ζ	Significant ratio of the current and mean change.
a_t	Class label for motion feature vector.
$h(\cdot)$	Expansion function to transform non-linear input features.
m	Mean vector for state in HMM.
n_j	Learning rate or node count.
$tr(\cdot)$	Trace of a matrix.
$\dot{\Phi}_B$	Derivative of the centered data matrix Φ_B .
AIP	Anterior Intraparietal area.
ED	Eigen Decomposition.
HMM	Hidden Markov Model.
Inc-KSFA	Incremental Kernel Slow Feature Analysis.
IPL	Inferior Parietal Lobule.
IT	Inferior Temporal Lobe.
LIP	Lateral Intraparietal area.
MNS	Mirror Neuron System.
PbD	Programming by Demonstration.
PFG	Parieto Frontal Gyrus.
SFA	Slow Feature Analysis.
STS	Superior Temporal Sulcus.
SVD	Singular Value Decomposition.
TGAR-AM	Topological Gaussian Adaptive Resonance Associative Memory.
TGAR-HMM	Topological Gaussian Adaptive Resonance Hidden Markov Model.
TGARM	Topological Gaussian Adaptive Resonance Map.
VIP	Ventral Intraparietal area.

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Appendix A: Publications

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CHAPTER 1 – INTRODUCTION

1.1 Imitation Learning

Learning by imitation, also known as Programming by Demonstration (PbD) provides a means for more natural human-robot interaction and is potentially the primary form of teaching (Nehaniv & Dautenhahn, 2007). Imitation is an advanced social learning behaviour whereby an individual observes and repeats another's behaviour. Even at a very young age, infants learn to control their bodies and execute tasks by watching others performing these tasks (Jones, 2009; Meltzoff & Gopnik, 1994; Trevarthen, 1979). Neonates are capable of imitating facial gestures and whole bodily movements; they gradually develop more complex imitative capabilities during interaction with their environment (Shon, Storz, Meltzoff, & Rao, 2007; Ray & Heyes, 2011; Meltzoff & Decety, 2003). Neonates between 12 and 21 days of age have been found to imitate both facial and manual gestures (Meltzoff & Moore, 1997) while older children can perform complicated forms of imitation (Meltzoff & Decety, 2003).

Due to the recent developments in robotics, the robots are able to move and act in human-centred environment, taking part in our daily lives. This has introduced the need for building robotic systems equipped with behaviour learning capabilities. Unlike humans, robots have limited capabilities to learn from their environment as robots need to be programmed according to specific applications. Due to the multifariousness of actions to be executed and the range of possible interaction with objects and humans, it is not feasible to explicitly pre-program a robot with such capabilities. From a robotic perspective, learning by imitation is of great interest as it provides a potential means of autonomous programming of complex systems without extensive trials. A human demonstrator can show an illustration of the task, while the robot learns and performs this similar task

imitating the human demonstrator. The key aspect of imitation learning is to obtain a generalized representation of a movement task from demonstrations of the teacher. This representation allows the robot to translate the perceived behavior in its own motor commands and repeat the observed task as close as possible.

A robot can be more than a passive observer of the world as it learns and develops (Edsinger & Kemp, 2006). Ideally, a robot would incrementally discover what it could control and adapt its perceptual and motor systems to this discovery. An essential prerequisite for imitation is a connection between the sensory systems and the motor system such that precepts can be mapped onto appropriate actions (Schaal, 1999). However, the matching mechanism between agents with different embodiment is not obvious. This mapping process is more complex than pure object recognition because it is necessary to understand how the imitator matches the observed action with its own body structure (Brass & Heyes, 2005). Selecting suitable motor output for a desired action requires learning the relationship between particular motor commands and accompanying sensory feedback that ensue as a result of those movements for humanoid robots (Erdemir et al., 2008).

The body of neonate is an elementary object of apprehension and exploration from the beginning. From birth, infants are diligently involved in investigating and learning about their environment. Similarly, these neonates are also involved in exploring themselves. They are not only discerning and recognizing themselves during the process of perceiving environment and objects, but they are also exhausting most of their active time systematically exploring their own body and instantly experiencing the effects of their own actions (Rochat & Striano, 2002). From an early age newborn exhibit exploratory commotion that appears to be particularly pointed towards the discovery of their own body attributes and features (Butterworth & Hopkins, 1988; Neisser, 1991; Rochat, 1998). They nudge themselves, or move their hands and/or limbs within the field

of view of visual exploration. Self-exploration is conceivably regarded as a behavioral inventory mechanism: *“It is a specific process through which infants become perceptually attentive to their own body and engage in a perceptual dialogue with themselves”* (Rochat & Striano, 2002). Simulating similar developmental processes in robots could provide important insights in investigating the use of cognitive and neural mechanisms in robotic environment. The notion of following a developmental pathway similar to those of neonates should pave the route for autonomous and human-like behaving robots.

1.2 Research Hypothesis

Most developmental theories emphasize that social interactions, in particular understanding of other individual’s actions, could be first achieved through imitation, yet the discussion on the origin of primitive imitative abilities is often neglected, referring instead to the possibility of its innateness (Slater & Kirby, 1998). Thus, our computational model for development of mirror neuron system is based on the hypothesis that *infants/robots acquire mirror neuron system as induced by sensorimotor associative learning through self-exploration. In other words, motor babbling could induce acquisition of sensory-motor associations capable of sustaining early imitation skills.* Self-exploration is regarded as a procedure by which infants become perceptually observant to their own body and engage in a perceptual communication with themselves. In our proposed hypothesis, we assume that crude sense of self is the prerequisite for social interaction.

1.3 Motivation

The idea of learning by imitation has inspired in the way humans and other animals learn. Therefore, current research is motivated from neurophysiological and psychological findings and discoveries on imitation in humans, chimpanzees and other primates to design and develop a computational systems capable to imitate and learn.

1.3.1 Self-Exploration – Meltzoff Theory

Imitation plays a major role in human development and especially for development and learning of new motor skills. Several studies indicate that imitation ability emanates early in life, and is considered as the major mode of learning for infants and adults (Aschersleben, 2006; Anisfeld, 1996; Bertenthal, 1996). A significant precursor to learning by imitation is to learn “*how specific muscle movements achieve various elementary body configurations*” (Rao et al., 2004). This helps the child learn a set of “motion primitives” that could be used as a basis for imitation learning.

Developmental psychology theorists point out two opposing hypotheses concerning the origins of self-concepts in infants. One view considers the fact that the infant learns about itself primarily through interaction with others (Cooley, 1992; Mead, 2009). Infants have no prior self-concepts and learn about the possibilities and powers of their own actions through observing the reactions of others to their behavior. On the contrary, other theorists assert that rudimentary concept about self-exists prior to such social experience (Butterworth, 1999; Meltzoff, 2007b). According to this hypothesis (referred to as Meltzoff theory), a primitive sense of self is the prerequisite for successful social interaction rather than an outcome of it. According to Meltzoff theory neonates do not innately understand what muscle movements attain a particular goal, such as tongue protrusion or lip protrusion. It is hypothesised that such movements are learned through an early experiential process involving random trial-and-error learning. In view of Meltzoff theory, infants have a proprioceptive sense of self that derives in part from their own body movements which the authors (Meltzoff & Moore, 1997) have called ‘body babbling’. Body babbling is the process of learning how specific muscle movements achieve various elementary body configurations. The approach adopted in proposed method is to develop an imitative mechanism for learning primitive concepts through self-exploration similar

to the human infant does.

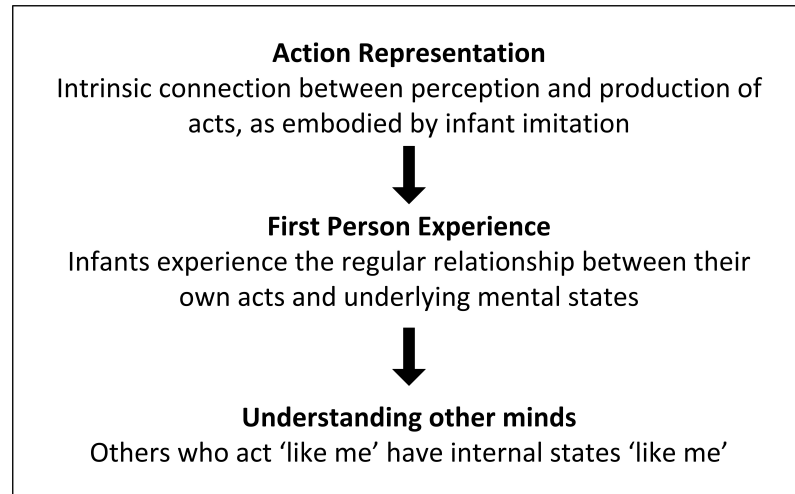


Figure 1.1: Like-me developmental framework (Meltzoff, 2007).

The concept of self-learning put forward by Meltzoff & Decety (2003) arguing about the developmental model of learning, stating that human infants monitor their own body via proprioception and associate their acts-as-felt to the acts-as-seen in others. Figure 1.1 provides an outline for the advised developmental path. Exteroception (perception of the acts of others) and Proprioception (perception of one's own acts) are coupled in development. The conjecture develops on corroboration that infants are capable to imitate from nascence.

The process of imitation involves encoding the observed behavior or task, and subsequently transferring this knowledge onto one's own motor representation of the very same action. Prior to the emergence of imitation ability, the affordance relations need to be learned and some perceptual-motor associations need to be formed (Hauf et al., 2004; Aschersleben, 2006). Learning the affordance relations, by self-directed experience entails the learning process to associate motor commands with corresponding sensory-effects, which then serves to close the perception-action loop so that the infants can behave accordingly to produce the desired action effects. This is mainly provided through a self-exploration strategy through which the infant explores its own motor capacities, bio-mechanical constraints, and discovers the possible contingencies between its own body

movements and resultant sensory effects.

Self-exploration establishes the basic building block for almost all forms of learning based on action. Starting from day one, the newborn babies engage themselves in an active world where they observe and interact with others. From birth, infants experience contrasting perceptual and sensorimotor occurrences that conceivably inform them about their own body (Rochat & Hespos, 1997; Rochat & Striano, 1999; Aschersleben, 2006). They move their body parts to explore the regularities in their sensory-motor system; they discover the connection between their actions and the perceptual consequences (i.e., visual, auditory, etc.) those actions have in the body. Babies learn at an early age that their actions have an effect on their bodies (Gibson & Pick, 2000). However, in order to be able to understand the environment and its relation with the surroundings, they are required to discover their own bodies, which are primarily based on self-exploration of action-effect relations (Rochat, 1995). Using self-exploration, the infants actively get involved in random acts and observe the consequent changes in the perceptual world. They start developing associations between their motor commands and their resulting perceptual effects. The ability to imitate builds upon the development of visuo-motor contingencies, and self-concept of one's own body's constraints and capabilities (Von Hofsten, 2004). Applying this approach, which is derived from the way human beings learn, will greatly enhance the usefulness and ability of robots in the human environment.

1.3.2 Mirror Experiment in Self-Exploration

Body image is fundamental for manipulation and it is extremely adaptive in animals. Kinaesthetic-visual correspondence is the recognition of resemblance amongst the notion of one's own body's extent and movement (proprioception) and how it appears (vision). This ability helps in recognizing that the visual images of their body in the mirror look like their body during movement. This involves a conversion of the egocentric

perspective to the allocentric one. There are two potential scenarios of the transformation between the representation of the observer and demonstrator (Sudo et al., 2012). One possible strategy is that the observer perceives and imitates the demonstrator as if looking in a mirror “*mirror image imitation, where, for example, the demonstrator’s right hand corresponds to the imitator’s left hand*” Sudo et al. (2012). Alternatively, the observer might approximate the demonstrator’s action utilizing the anatomically congruent limb “*anatomic imitation, where, for example, the demonstrator’s right hand corresponds to the imitator’s right hand*”(Sudo et al., 2012).

Lewis et al. (1989) suggested that human infants seem to become self-aware when they begin to recognize and discern themselves in a mirror. Physiological experiments (Gallup, 1970; Bekoff & Sherman, 2004; Elshaw et al., 2004; Premack & Woodruff, 2010; Bahrack & Watson, 1985) show that these observations provide a link between mirror image and self-awareness. To assess the mirror self-awareness, Gallup (1970) and Amsterdam (1972) applied a tool referred to as mirror test. They have discovered that infants observe their own body movements in front of the mirror to explore specific kinaesthetic-visual egression of their action consequences. Similarly, Bahrack & Watson (1985) using a habituation paradigm, established that five month old infants especially look at non-contingent perspectives of their bodies which have contradictory visual and kinaesthetic cues, since in this non-congruent view there is a violation of the familiar visual-proprioceptive notion of body movements.

The mirror test not only plays an essential role in the analysis of animal behaviour, but it also reveals insight into the development of self-awareness in humans (Premack & Woodruff, 2010). When presented with an image of its own body that is temporally contingent with its movement, such as reflection in the mirror, a human infant displays signs of self-exploratory behaviour from three months of age onwards. Another theory for self-recognition proposes that mirror self-awareness comes from corresponding physical

(kinaesthetic) experience to visual feedback (Mitchell, 1997). Based on the later hypothesis, the kinaesthetic-visual matching is the recognition of similarity between the feelings of one's self body movement (proprioception) and how it looks (vision). A similar hypothesis has been outlined as the associative sequence learning (ASL) model (Heyes & Bird, 2007; Catmur et al., 2009) which hypothesizes that the correspondence problem between demonstrator and observer is solved through the sensorimotor experience acquired during development via processes of associative learning.

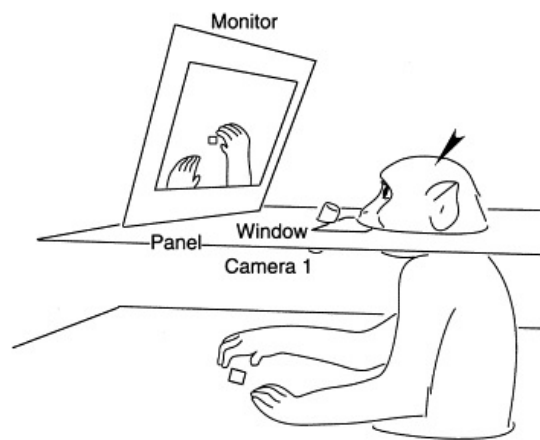


Figure 1.2: Perception of body in monkey (Iriki et al., 2001). The monkey was trained to retrieve a food item by watching their hand movements through a real-time video monitor.

Iriki et al. (2001) found visuo somatosensory neurons (bimodal neurons) in monkey intraparietal cortex that incorporated a tool into a mental of the hand. The authors trained a monkey to recognize the image of the hand in a video monitor and demonstrated that the visual receptive field of these bimodal neurons was projected onto the video screen (Figure 1.2). The experimental results suggest that the coincidence of movements between the real hand and the video-image of the hand movements. In summary, these experiments suggest that the monkey's body perception is developed through motor learning (Maravita & Iriki, 2004).

1.3.3 Mirror Neurons

From a biological perspective, many neuroscientists regard imitation as mediated by mirror neurons in humans (Oztop et al., 2006). Mirror Neurons belongs to the family of visuomotor neurons which were originally discovered in the F5 area located in the pre-motor cortex of the macaque monkey brain (Pellegrino et al., 1992). Mirror neurons not only activate when the primates observes a meaningful action (e.g., grasping) performed by demonstrator (human or monkey) and also activate when the primates try to execute the same observed action (Gallese et al., 1996; Rizzolatti et al., 1996; Rizzolatti & Lupino, 2001). Furthermore, it has been proposed that the functionality of mirror neurons may be extended from action recognition to encoding the intention of the demonstrator (Iacoboni et al., 2005). The experiments conducted by the neurophysiologists showed that these mirror neurons are characterized for the control of goal directed hand movements such as reaching and grasping and have both motor and sensory properties (Craighero et al., 2007; Fadiga et al., 1995). Another type of neurons which belongs to the same family of visuomotor neurons are Canonical Neurons, also known as object observation-related visuomotor neurons (Gentilucci et al., 1988). These neurons are like mirror neurons in motor properties, but do not respond to action observation. These neurons encode the shape of the object and respond to the objects presentation in terms of motor commands (Murata et al., 1997). These canonical F5 neurons are believed to control the execution of goal-aimed actions and translate the visual information into the type of motor response required for a certain object.

Rizzolatti & Sinigaglia (2010) summarized mirror neuron function as ascribed to the “parieto-frontal action-observation action-execution brain circuit” or the mirror neuron system (MNS). The schematic interpretation of the mirror neuron system and its relevant circuitry connections are depicted in Figure 1.3. The mirror neuron system comprises

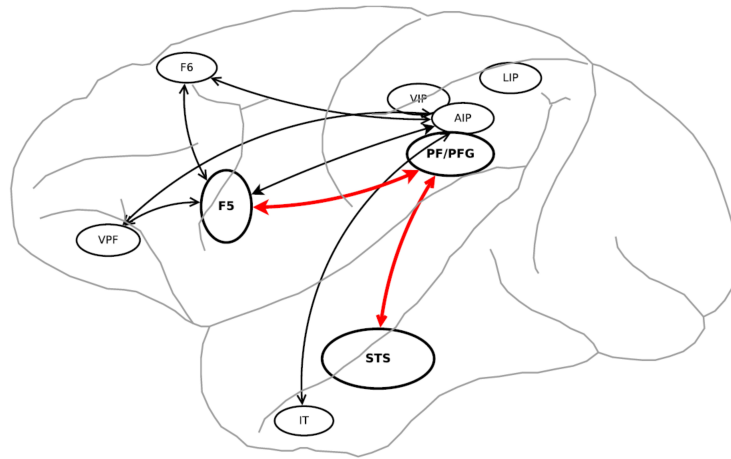


Figure 1.3: Schematic illustration of MNS in the macaque monkey brain. Area F5 is connected with the inferior parietal lobule (areas AIP-anterior intra-parietal, PF and PFG). Within the frontal lobe, area F5 is connected with hand/mouth representations of primary motor cortex (Source: Craighero et al. (2007)).

of the area F5, area Parieto Frontal Gyrus (PFG) in the rostral part of the Inferior Parietal Lobule (IPL) between areas PF (Cytoarchitectonic division of the macaque inferior parietal cortex) and PG (Cytoarchitectonic division of inferior parietal cortex), and the Anterior Intraparietal area (AIP). Both parietal areas are attached with F5 and both receive visual information from areas located inside the Superior Temporal Sulcus (STS) and the Inferior Temporal Lobe (IT) providing input to frontal motor-control area F5. Similarly to F5 region, STS encodes motion, however, it is derived of motor properties and consequently cannot be regarded as a true part of the mirror neuron system, which applies for inferior temporal lobe as well. The parieto-frontal circuit is also linked with the area F6 (pre-supplementary motor area) and the ventral prefrontal cortex, which are the higher-order areas that control it. Furthermore, neurons with mirror attributes were detected in other areas of the parietal lobe, the Lateral Intraparietal area (LIP) and Ventral Intraparietal area (VIP). Neurons in ventral intraparietal area encode haptic and visual stimuli happening in peripersonal space and conceivably responsible for encoding bodily-directed motor acts instead of object-aimed motor acts represented by mirror neurons in F5 (Ishida et al., 2010).

Rizzolatti & Arbib (1998) suggested that mirror neurons area F5 in the monkey is homologous to human Brocas area. They proposed the Mirror System Hypothesis (MSH) stating that action recognition is a primary step towards the inter-individual communication and leads to the development of speech and the evolution of language. Another functionality of mirror neuron presented by Gallese (1998) is to emphasize the process of mind reading, i.e. representing the mental state of demonstrator through simulation of mind in terms of goals or perceptions. A similar modelling mechanism have been proposed by Gallese (2007) supporting the idea of embodied simulation. This mechanism presents the idea that the observer just do not see the action, but also the sensory description of the observed stimuli, the internal representation of the observed action, emotions, and sensations as if the observer is performing the observed actions. However, no further details have been provided by the authors and in the literature on implementation of these proposals.

Mirror neurons were divided into three categories based on their congruence between visualized and executed actions: strictly congruent, broadly congruent and non-congruent (Gallese et al., 1996). When both the effective observed and effective executed actions match and represent the action's goal and the method of action execution, the neuron is termed as "strictly congruent" mirror neuron. While in the broadly congruent neurons, the executed actions do not require to be the same as the observed action. The broadly congruent mirror neurons suggest that these cells provide a flexible coding of actions of self and others, which is an important property for successful social interactions (Iacoboni, 2009).

The discovery of mirror neuron and their functional hypothesis presented in the literature suggests that these neurons formed the foundation of action understanding (Umiltà et al., 2001), motion imitation (Arbib & Bonaiuto, 2008) and language development (Cor-

ballis, 2010). Neurophysiological and brain-imaging experiments² show the evidence that a mirror-neuron system (MNS) exists in humans (Rizzolatti & Craighero, 2004). The discovery of mirror neurons has induced significant interest in action observation and imitation among cognitive neuroscientists (Rizzolatti & Buccino, 2005; Iacoboni, 1999).

1.3.4 Origin or Development of Mirror Neurons

There are several hypotheses concerning the origin of mirror neurons, which tend to contradict with one another. First is the evolutionary hypothesis (Rizzolatti & Arbib, 1998) which states that the ability of mirror neurons to match the observed and executed behaviours is genetically inherited and that the experience has minor significance in their development. Opposing the evolutionary hypothesis, Heyes (2010) proposed the association hypothesis, which states that mirror neurons are a by-product of associative learning. According to the association hypothesis, the motor commands and the sensory data which causes these motor commands are associated through in the memory. The associative memory, which was formed in the past, is triggered by a sensory (visual) stimulus when the observer executed the particular action with perceptual guidance.

A similar hypothesis to the one of associative hypothesis is the Hebbian account (Keysers & Perrett, 2004). They assert that the actuality of mirror neurons can be described on the basis of anatomical connections between mirror circuitry in the brain regions (as mentioned in Figure 1.3) and the Hebbian rule. However, Heyes (2010) criticises that the Hebbian learning only indicate contiguity, whereas the associative hypothesis involves both contiguity (the closer the two events occur in time, the stronger the association) and contingency (correlation between the events).

²For a review of these experiments refer to (Turella et al., 2009)

1.3.5 Imitation and Mirror Neurons

Functional properties of mirror neurons suggest that mirror neurons are important part of imitation and many neuroscientists regard imitation as mediated by mirror neurons in humans (Rizzolatti & Buccino, 2005). However, there is a great discussion about the monkey's ability to imitate leading to a major consensus that monkey do not imitate or have limited capability. Humans can exhibit complex imitation because human mirror neuron system is capable of rich forms of imitation (Iacoboni, 1999). Understanding of an action is very important for imitation, otherwise the imitator will perform meaningless action. Typically, mirror neurons do not fire when the organism observes an action without involving target object. Similarly, they also do not activate when the primates only observe the target object without observing any action (Uithol et al., 2011; Newman-Norlund et al., 2008). Thus, action understanding or recognition is based on the recognition of the goal position or object. The connective role of mirror neurons for action observation and execution made it a suitable candidate for various imitation theories. Mirror neuron system is considered as the ideal mechanism of imitation by transforming observed actions into the appropriate motor actions and is involved in repetition of action performed by others (demonstrator) (Heyes, 2001; Buccino et al., 2004).

1.3.6 Action Understanding and Mirror Neurons

The action-understanding feature supported by mirror neurons is considered to be the basis of imitation (Rizzolatti & Luppino, 2001). For understanding the action of others, two hypotheses were discussed by (Rizzolatti et al., 2001) – the visual hypothesis and the direct-matching hypothesis. According to these hypotheses, the action understanding is either based on the visual analysis of the action without motor association or by mapping the observed action onto the self-motor representation. The visual hypothesis relies on the visual analysis of the observed action and its relation with the objects

in the environment, whereas, the direct-matching hypothesis maintains its theory on the sensory-motor mapping, i.e., mapping of the observed action on the observers own motor representations.

In cognitive science there are two main theories of action control (Iacoboni, 2009). The first theory called the sensorimotor theory states that actions appear only as a reaction to external stimuli. Based on this theory, perception and motor control are disparate from each other. The external stimuli are rendered into motor commands by mapping the stimulus response. From imitation and action understanding perspective, the sensorimotor approach suffers from the *correspondence problem* in which the observer requires to translate the visual sensory representation of the observed behavioural action into his own motor representation for that particular behaviour (Nehaniv & Dautenhahn, 2002; Alissandrakis et al., 2003). From a computational approach, this kind of translation is very important because the imitator and demonstrator may not have the same physical body structure. On the contrary, the ideomotor theory of action primarily assumes that perception domain and motor domain share common neural structure. According to the ideomotor proposition, actions are initiated by sensory consequences that typically resulted from them, in other words, by the anticipation of their effects. Actions are represented on the basis of perceptual aspects that are usually present during their execution. The association between actions and perception indeed has to be learned through experience.

1.3.7 Invariant Properties of Mirror Neurons

The variant and invariant properties of mirror neurons have been recently recognized (Caggiano et al., 2009) also in responses of the mirror neurons area of monkeys' brain. The neurons in STS are sensitive to viewpoint from which the action is observed, but also there are neurons that are invariant to it (Perrett et al., 1991). How these neurons acquire this property is not entirely clear (Keysers & Gazzola, 2014), but in monkeys

such viewpoint invariance can emerge after experiencing different perspectives of the same three-dimensional object (Logothetis & Pauls, 1995). Accordingly, it might be the opportunity to see the actions of others from a number of perspectives that endows neurons with the capacity to respond to the sight of actions across perspectives. The sight of the action could then trigger matching motor actions because it triggers activity in the same audiovisual neurons that have been linked to the observer's motor command during body-babbling.

Superior temporal sulcus (STS) of the brain plays an important role in action understanding and mirror neuron system functionality (as mentioned in Sec.1.2.1). STS is one of the primary sources of visual information for the area comprised of mirror neuron system. Area F5 is divided into two parts: F5c (F5 convexity) and F5a (F5(bank) anterior) (Nelissen et al., 2011). STS is linked with F5 via two different pathways (Bonaiuto et al., 2007; Nelissen et al., 2011). The posterior part of STS denoted as STSp is linked with F5c via PF pathway (PFG) and the anterior part of STS called STSa is linked with F5a via AIP. STS shows great deal of interesting properties of the brain with topologically distinguished categories of neurons. For example the lower part of STS is responsible for encoding the biological movement, whereas the upper part encodes the identity of the observed individual and groups of observed actions. Along with these properties, the neurons in STS are sensitive to viewpoint or visual perspective from which the object is perceived (viewer-centered) (Perrett et al., 1991), but also invariant to it (view-invariant or object-centered) (Caggiano et al., 2009).

Perrett et al. (1991) investigated that different types of STS neurons represents different perspectives of an object or action provide information to the invariant neurons. This appropriates the invariant neurons to respond to the movement/object irrespective of the observers' view-point and render a high-level categorical representation. This phenomenon is referred to as the response pooling of lower-level units towards higher-level

units. It has also been shown that these invariant or object-centered neurons have distinct anatomical position inside the superior temporal sulcus. Neurons discerning to the view-point are located in posterior areas (STSp) and the neurons related to view-invariant are positioned in anterior areas of STS (STSa), which are adjacent to frontal cortices. This anatomical disposition of having general representation in locations near to frontal cortex not only pertains to STS, but also to other parts of the parietal and prefrontal lobes, such as motor (mirror neuron) areas.



Figure 1.4: Illustration of three points of view representing the responses of mirror neurons. (Source: Caggiano et al. (2009)).

Furthermore, variant and invariant properties of mirror neurons have been recently recognized by Caggiano et al. (2009), also in responses of the mirror neurons in F5 area of monkeys' brain. In their experimentations, monkeys observed grasping actions filmed from three different perspectives, namely the self-observing view (0deg), the side view (90deg) and the opposite view (180deg), (Figure 1.4). Caggiano et al. found both variant and invariant mirror neurons.

1.4 Research Objective

Drawing inspiration from self-exploration in infants (Meltzoff & Moore, 1997) and associative hypothesis about development of mirror neurons (Catmur et al., 2009), the objective of this thesis is to:

- Develop an imitation system that enables a robot to autonomously learn primitive

concepts through self-exploration using body babbling with no a priori knowledge of its motor system or the external environment.

- Develop a computational model of mirror neuron system to permit the robot to associate the perceived self-performed action with actions in its own (self) motor repertoire empowering it to understand the perceived movement by taking into account the view-dependency as a probable outcome of their associative connectivity.

1.5 Technical Challenges

In designing an incremental imitation learning system I have addressed the following fundamental issues:

- During a continuous interaction, how a robot can autonomously segment and determine the start and end of the action using on-board vision sensors without relying on the a priori information about the kinematic model of the demonstrator?
- How the model can retain previously learned data and also incrementally acquire new knowledge in a self-organizing manner without corrupting previously learned data for easy and efficient retrieval.
- How to select the structure for the probabilistic model i.e., estimating the number of states to efficiently encode the sensory data without restricting the learning capabilities of the robot.
- How do allocentric visual representations of actions become associated to their corresponding motor representations? In other words, how do we develop knowledge about visuomotor correspondence?
- How to associate the observed self-exploratory action with appropriate motor commands focusing on the actions performed by the demonstrator rather than the view-

point from which it is observed?

1.6 Problem Description

A critical problem in imitation learning is the '*visuomotor correspondence problem*' (Brass & Heyes, 2005), in which the observer requires to translate the visual sensory representation of the observed behavioural action into his own motor representation for that particular behaviour (Nehaniv & Dautenhahn, 2002; Alissandrakis et al., 2003; Asada et al., 2006). In other words, *how are we able to develop a link between visual representations of actions to their corresponding motor commands?* In order to solve this issue, it is essential for the observer/imitator to develop a mapping of its own body so that it can associate an observed action with the corresponding motor commands.

The behavior patterns are considered as a sequence of motion primitives (Schaal, 1999), atomic parts of a behavioral sequence. For example, if the demonstrator is performing a fighting action, then each motion sequence may correspond to a simple move, such as kick or punch. These basic actions, when combined together form a variety of actions, are specified as motion primitives. Humans spontaneously segment actions by identifying its boundaries as they view others behavior (Zacks & Swallow, 2007). The automated segmentation of observed action sequences into plausible meaningful behaviors is a main problem in online imitation learning. Most of the motion segmentation algorithms for robot learning rely on joint angles (Takano & Nakamura, 2006; Kulic et al., 2008; Meier et al., 2012) and very less focus was given to segment motion patterns directly from the vision (Kulić et al., 2009). The motion capture system are utilized to measure the joint angle data of the demonstrator, and this information is then employed for motion primitive segmentation. Although motion capture data provides accurate calculations of the observed motion, however, the space requirement and expense of such systems are significant limitations, and prevent the use of such systems for long term

data gathering. Therefore, it would be advantageous if the robot could analyse observed motion data obtained from on-board vision sensors.

When a robot is in an environment with humans, some novel events may be encountered by the robot, which were not learned previously. This will make the robot ineffective for such dynamic environments. Therefore, the robot must be capable of updating these changes so that it can adapt itself efficaciously to novel situations encountered during learning. A natural way of representing these behaviors by the robot is through the use of probabilistic models. Hidden Markov Models (HMM) (Rabiner, 1989), originally developed for speech recognition and speech synthesis, have been widely used for human motion recognition and generation. HMM takes sequential data as input and generates the probabilities. The ability of HMMs to generalize human demonstrations has led to the development of several methods for HMM based movement recognition and generation (Calinon & Billard, 2004; Inamura et al., 2004). However, most of these methods operate off-line where the model structure is static and determined beforehand. In off-line or batch learning methods, the motion patterns are processed sequentially. Such interaction might seem a bit artificial since the patterns are predefined by the designer. Therefore, the stochastic model should allow new information to be incorporated incrementally without corrupting previously acquired data.

Another issue associated with the well-established learning algorithms based on stochastic models such as HMM or Gaussian Mixture Models (GMM) (Billard et al., 2006; Kulic et al., 2007a) is in estimating the structure of the model. Setting up the appropriate number of states in the model is difficult because the number of motion patterns in the data is unknown. If there is a smaller number of states than the observed trajectory components, the model cannot explain the patterns considerably. On the contrary, if the number of model states is large, the system will require too much training data and excessive computational requirement. Thus, the major question is to find a suitable model

structure that would best approximate the given environment without loss of information. In literature the structure of HMM (i.e. the number of HMM states) is either chosen manually or using other methods such as Bayesian Information Criterion (BIC) (Calinon & Billard, 2004) or Akaike Information Criterion (AIC) (Kulic et al., 2007b). This limits the number of motion patterns to be learned a priori and results in a trade-off between model fitness and number of parameters. Thus such methods are not suitable for incremental learning.

1.7 Research Contribution

I adopted a cognitive science perspective with the hypothesis that automatic imitation of simple and complex actions can emerge from the intrinsic properties of a neural associative network fed by spontaneous actions and visual feedback of these actions available during motor babbling.

Inspired by the classical mirror test, in this work I will demonstrate that it is feasible to carry out vigorous self-exploration on the basis of matching kinaesthetic experience to visual motion alone. In my mirror experiment, a humanoid robot stands in front of a glass mirror in order to obtain the associative relationship between his own motor generated actions and (a mirror image) of his own visual body-image. Through self-exploration, the humanoid robot incrementally learns the mapping between body image and corresponding motor actions by standing in front of the mirror, executing actions, and processing the visual images of the body it observes.

I developed an algorithm for automatic segmentation and clustering based on the image sequences captured from the robot's on-board vision sensors for temporal segmentation of actions. The observed actions are segmented into episodes of different actions determined by the start and end of actions. This part is achieved using Incremental Kernel Slow Feature Analysis (Inc-KSFA) algorithm. Incremental SFA framework extracts

slow varying features from input signals. The variation of slowly changing features is exploited to determine the occurrence of different activities in an online and incremental fashion. Complex behavioural actions are learned by the combination of various motion primitives to generate complex actions based on their observations (Nicolescu & Mataric, 2003; Billard et al., 2008). Similarly, in our work, a new behaviour is created from a combination of two or more motion primitives learned during self-exploration..

For incremental learning I proposed novel Topological Gaussian Adaptive Resonance Hidden Markov Model (TGAR-HMM). In the proposed architecture, the structure of the model is updated incrementally based on the observation sequence and estimate all the required probabilities in an incremental and an on-line manner. The proposed model also acquires new information without corrupting previously learned data in a stable and a self-organizing fashion. This mechanism is accomplished by developing a novel probabilistic neural network architecture based topological mapping algorithm; called Topological Gaussian Adaptive Resonance Map (TGARM). This compactly describes the environment as a collection of nodes linked by edges. Each node represents the motion elements symbolized through joint angle values. During the topological mapping, the motion elements are arranged in the form of nodes connected with edges.

After generation of these maps (vision and behavior/action) independently, the visual space and the behaviour space are connected using an associative memory. In order to create an association between the observed visual features (visual space) and self-motor actions (behaviour space), I developed an incremental associative memory architecture called Topological Gaussian Adaptive Resonance Associative Memory (TGAR-AM). Once the association is developed and learning is completed, a partner robot comes before the robot performing the similar actions as previously learned by the robot. Based on the sensorimotor association, the robot recalls the corresponding observed motion pattern from the memory developed during self-learning step and performs the actions.

1.8 Overview of Thesis

The remainder of the thesis is organized as follows:

Chapter 2 reviews related work on mirror neurons. The survey begins with discussing various biologically realistic computational models of mirror neurons, then proceeds to imitation learning in the area of robotics.

Chapter 3 gives a detailed overview of proposed architecture for mirror neuron and imitation learning.

Chapter 4 explains the developed algorithm for automatic temporal segmentation based on the image sequences captured from the robot's on-board vision sensors. The observed actions are segmented into episodes of different actions determined by the start and end of actions.

Chapter 5 explicates the proposed incremental learning architecture through novel Topological Gaussian Adaptive Resonance Hidden Markov Model (TGAR-HMM). In the proposed architecture, the structure of the model is updated incrementally based on the observation sequence and also estimate all the required probabilities in an incremental and an on-line manner.

Chapter 6 proposes incremental topological associative memory architecture for the development of sensory-motor association acquired through self-exploration.

Chapter 7 explains the efficacy of the proposed framework through simulation and real-time robotic implementation.

Chapter 8 summaries the discussion of the results obtained and of the practical and theoretical significance of the proposed framework along with some directions for the future work.

CHAPTER 2 – LITERATURE REVIEW

Mirror Neurons and mirror systems are an important breakthrough in the brains of animals and humans providing a sensory-motor mapping. Mirror neurons found in the brain of macaque monkey not only fire when the monkey observes an action but also activates when the monkey performs the similar action. Brain imaging studies reveals the presence of mirror neuron system in the human brain (Mukamel et al., 2010). Several functional features of mirror neurons have been proposed in literature emphasizing their role in action understanding, language development, mind simulation, and imitation. The discovery of mirror neurons leads a great deal of robotics research in investigating the ability of robot to interact with human and its environment. This chapter provides a comprehensive overview of various computational models of mirror neurons and the research works on human motion imitation models inspired or adapted from the mirror neurons.

This chapter provides a comprehensive review of the state of the art motion imitation models. The concentration is largely on the imitation models which are either explicitly or implicitly based on mirror neurons. I have discussed various types of models of mirror neurons and also the approaches designed for motion recognition and generation particularly focusing on robotic applications. The chapter is divided into three main sections based on the taxonomy shown in Figure 2.1. The first section discusses the biologically realistic models of mirror neurons dealing directly with modelling the brain functionality (not necessarily linked to imitation). The second section deals with the robotic imitation models associated with the mirror neurons. Finally, the third section deals with the robotic imitation models related to the temporal sensorimotor learning.

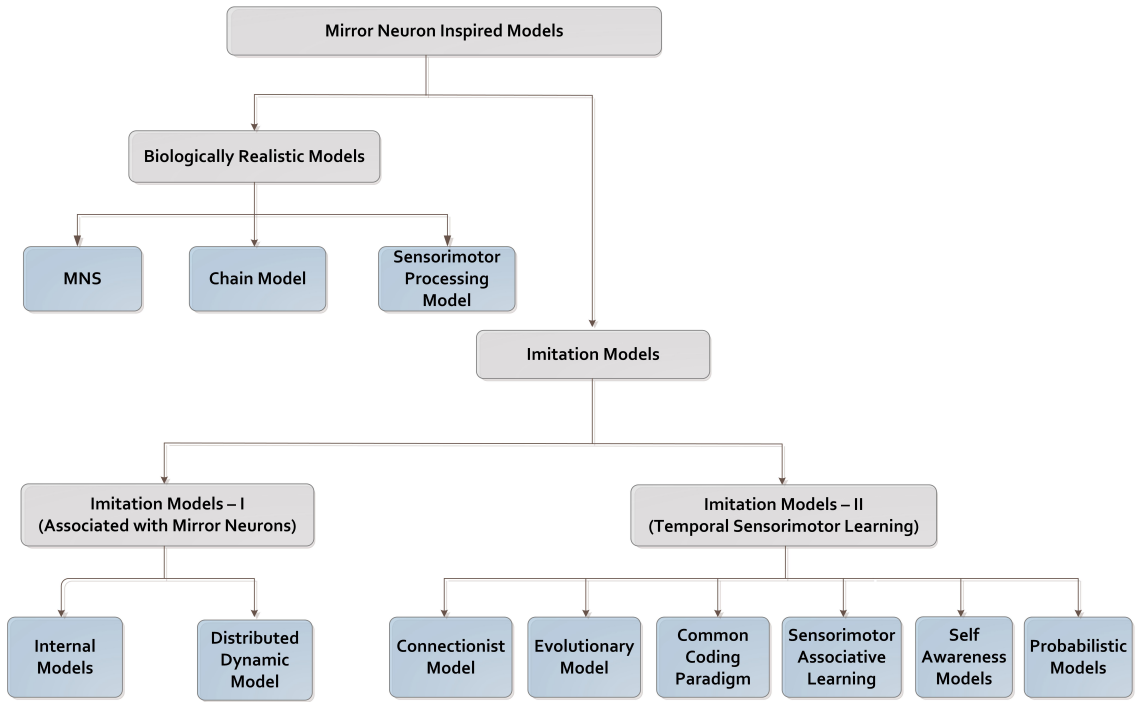


Figure 2.1: The taxonomy of methods developed for this review.

2.1 Biological Realistic Models of Mirror Neurons

2.1.1 Mirror Neuron System - MNS

The Mirror Neuron System (MNS) proposed by Oztog & Arbib (2002) was designed to relate activity in canonical and mirror neurons by encoding the grasping activity configuration with visual input. The property of mirror neurons is exploited through the system's ability to relate the self-observation to the recognition of actions performed by others during grasp related activities. Instead of utilizing the visual analysis, the core mirror circuit is based on the mechanisms that can recognize an action in terms of the hand state, a representational component, which makes an explicit relation between the hand trajectory hand and the affordances of an object. The activity of mirror neurons, modelled by an array of neurons, was determined by the type of grasping behaviour. They show that a feedforward two-layer neural network with perceptron units, representing the core mirror circuit, could be trained (by the error back-propagation algorithm) to recognize the grasp type from the hand-state trajectory. The input layer of the neural network corresponds to the action affordance-hand state association schema while the output layer of

2.1.2 MNS2 Model

Biologically plausible mirror neuron architecture (MNS-2) was developed using Jordan-type recurrent neural network with sigmoidal activation function (Bonaiuto et al., 2007), which replaces the back-propagation neural network in MNS-1. The recurrent neural network was trained using back propagation through time (BPTT). As suggested by Umiltà et al. (2001) that the macaque monkey can recognize an action, even if the target object is hidden, the MNS-2 interpreted this scenario using a hypothesis for brain consisting of two working memories with dynamic re-mapping. One for the hand and object information and second for the object affordance. The neural network receives as inputs hand state representations. Another contribution of this model is extended to audio-visual mirror neurons. The auditory subsystem addresses the target objects which were not only based on visual gestures, but also on vocal articulations, supporting the hypothesis proposed by Kohler et al. (2002). There is a direct connection between the auditory and the corresponding regions in F5 and the neural network weights are modified using Hebbian learning to associate auditory input with corresponding action (Arbib & Bonaiuto, 2008). This allows the mirror neurons to react not only to vision but also to the associated auditory stimuli.

Another useful extension to the MNS2 model is the addition of “What did I just do” feature (Bonaiuto & Arbib, 2010). This theory is motivated by the example of cat reaching for food in a glass tube. A piece of food was placed in a horizontal tube facing the cat. In order to eat the food, the cat had to reach its paw into the tube, grasp the food, and bring the food to its mouth (Alstermark et al., 1981). After multiple trials of failure, instead of learning or refining of new skills, the modification in the cat decision making occurs to grasp the food. After spinal lesions affecting grasping with a forepaw, the cat re-learned to extract food from a horizontal tube in a different way than an unimpaired

cat. The MNS2 model utilises representations of the internal state (hunger) and external state (distances between objects) as inputs into the system. The system selects an action based on its desirability, calculated from the internal state, and its executability, computed from the external state.

The “What did I just do?” feature of MNS-2 helps in monitoring the assessment of the self-performed actions and observed action of the others. A hypothesis is developed that mirror neurons are active not only for the execution of self-action, but also for the efferent copy of the intended action, postulating a new property of mirror neuron to speed up the learning process of new motor programs. The hypothesis was tested using the system called augmented competitive queuing (ACQ) (Arbib & Bonaiuto, 2008). During the simulation, each action is recognized by its effects. The winner takes all (WTA) process activates the neuron representing the action with largest priority signal. This model was designed using augmented competitive queuing (ACQ) for relating the perceptual and motor schemas by using competitive learning. The model is implemented using leaky integrator neuron learned by temporal difference (TD) which is a type of reinforcement learning.

The extension of the MNS2 model highlights the fast reorganization ability of the MNS by approaching it in a cognitively plausible way (using reinforcement learning). The proposed computational mechanisms are therefore very interesting.

2.1.3 Chain Model

The Chain Model (Chersi, 2012) proposed a neural network architecture for action recognition and execution. The Chain Model hypothesized that motor and mirror neurons in the parietal and premotor cortices are organized in chains encoding motor acts and the final goal of the agent. In other words, every motor act belonging to an action is fluidly coordinated with the preceding and the subsequent one in form of a chain leading to a

specific goal action (Jeannerod, 1988; Rosenbaum et al., 2007; Fogassi et al., 2005). In every chain, each neuron coding a motor command alleviates the activation of the neuron encoding the next motor command of the chain, thus providing motor fluency to the complete action (Chersi, 2011).

These neurons are activated in a chain sequence starting from the parietal cortex encoding goal-specific task, propagating this activity in the premotor cortex computing movement specific information and finally propagating to the motor cortex where appropriate motor commands are generated and transferred to the spinal cord for execution. For sustainment of the activity the motor command information is back propagated to higher layers. Due to the duality of the model, the same mechanism of action execution is utilized for action recognition in mirror neuron chains.

The model is implemented using spiking neural networks in a robotic environment. Individual neurons are described by a leaky integrate-and-fire model. The learning rule is implemented using spike timing dependent plasticity (STDP). In the beginning neurons are randomly interconnected.

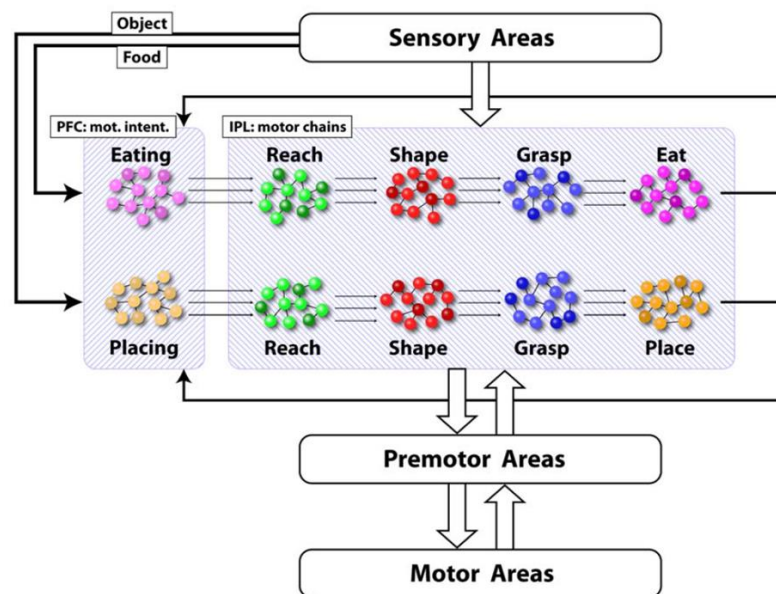


Figure 2.3: Schematic representation of the areas and the populations of neurons that is active during the motor task. The prefrontal cortex contains the motor intentions and thus acts as the chain selector, while sensory and motor corollary signals regulate the transmission of activity waves within the chains.

Chersi (2011) presented a mirror neuron model for understanding the role of the MNS in joint actions. The study is based on the hypothesis that MNS is involved in visual and motor understanding without requiring any agentic understanding (Pacherie & Dokic, 2006). Joint actions require interpreting the intentions of other's action; therefore, the original chain model is slightly modified where prefrontal cortex encodes the task-relevant information and the intentions of others. When an action is observed, the corresponding mirror chains are activated. The neural Chain Model reproduces the functional abilities of the mirror neuron system by taking into consideration the forward and inverse mapping of the sensory motor commands. From a biological mirror neuron perspective, the firing rate of different neuron was affected by the final goal of the action for e.g., grasping and reaching (Fogassi et al., 2005).

2.1.4 Sensorimotor Processing Model

Tessitore et al. (2010) proposed a computational model for mirror neurons based on the direct matching hypothesis suggested by Rizzolatti & Luppino (2001). The main idea behind this computational model is that the observer understands the action because the motor representation of the particular action is activated in the brain. This computational model hypothesized that mirror neurons are involved in the encoding of motor information for action recognition and control processes, enabling it to use mirror-coded motor information. According to this model the object-directed action is subdivided into distinct classes identified as set of vectors. These vectors span a subspace in the space of hand-joints configuration. In an action subspace, the hand-joint configuration is represented as a linear combination of these vectors. Thus, this computational model assigns the functionality of the mirror neurons in the selection of appropriate subspace. During the hand grasping action, the information about the hand configuration is used to form a priori hypothesis for the computation of associating or mapping from sensory and propri-

ceptive input to hand configuration motor coding. This mapping information is used to iteratively support the a priori knowledge along with the sensory input. The hand grasping configurations is modelled using eigenpostures calculated from principal component analysis. These eigenpostures are termed as action subspace. It has been assumed that the linear combination of these eigenpostures will result in different classes of hand grasping controls, for example “grasping with a precision grip” or “grasping with whole hand apprehension”. A perceptual system was developed to compute the visual description of the input data. This perceptual system solves the problem of assigning different perceptual, sensory data to the different hand configurations. This problem is assumed to be a multivalued function because different visually perceived data might lead to different compatible hand configurations. This association is modelled using the probabilistic approach, i.e., the mapping output is approximated by the unconditional probability density function. A motor-perceptual system was developed which use the perceptual information to make a selection from the action subspace. The motor-perceptual system was also modelled using the probabilistic approach by associating a probability value,(updated with input data), to every action in the subspace. In other words, the information coded by mirror neuron activity is assumed to be related to these probabilities.

The sensory-motor processing model is based on the direct matching hypothesis utilizing the motor information encoding in the mirror neuron system. This is in contrast to the other models of the mirror neurons system presented in literature. In this model, the motor information encodes action subspace probabilities, without requiring a precise reference to action kinematic parameters. This means that involvement of motor information operates on a higher (category) level when interacting with sensory processes, which resembles the level of Hebbian account (Keyser & Perrett, 2004; Farkas et al., 2011). This computational model only presents the role of mirror neurons in action perception; the problem of action execution is not discussed in this model.

2.2 Imitation Models

2.2.1 Internal Model of Imitation

The central nervous system internally represents a transformation from sensory signals to motor commands. The central nervous system uses internal models for movement planning, control, and learning (Kawato, 1999). This internal model consists of two forms; the inverse model and the forward models (Wolpert & Ghahramani, 2000). Inverse model maps the inverse relationship between the observed sensory actions and motor commands, whereas the forward model maps the relationship between motor commands and change in the environment based on the predictive information about the world dynamics. On one hand, the forward model predicts the sensory consequences of the motor commands; on the other hand, the inverse model computes the appropriate motor commands from the sensory data.

From mirror neuron perspective F5 mirror cells lie at the essential interface between forward and inverse models, which are represented by cells in STS (superior temporal sulcus), PF and F5 (Miall, 2003). Iacoboni et al. (2001) and Miall (2003) stated that during action observation the mirror circuit formed by the STS, PF and the ventral premotor cortex (STS–PF–F5) works as inverse model. Conversely, during action execution the reverse connections (F5–PF–STS) works as forward model (Figure 2.4). Various models have been proposed for sensorimotor control based on internal models.

The MOSAIC model (Wolpert et al., 1998; Haruno et al., 2001) is a modular architecture developed for motor learning based on forward and inverse models. In this approach, suitable forward-inverse controller is selected for the context from multiple controllers. The basic idea is that multiple inverse models control the system and each of these models is paired with corresponding forward model. The forward model predicts the results of a given motor command in a context, which is used to guide the learning

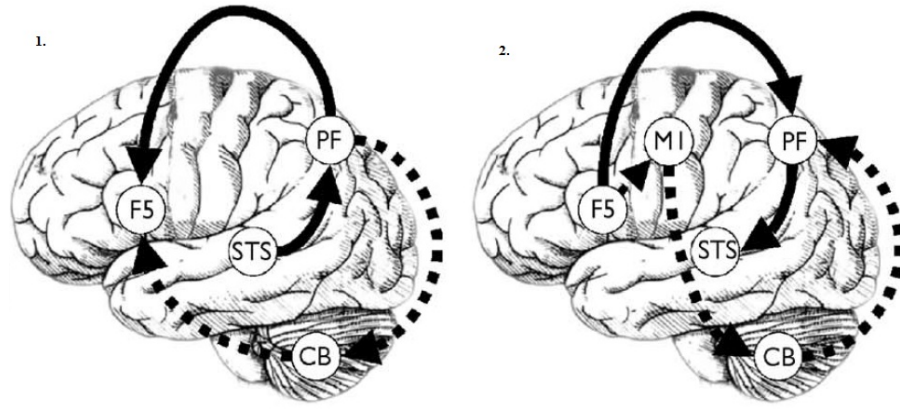


Figure 2.4: (1) Activity during observation of actions: The circuit linking STS, PF and F5 (solid arrows) may act as an inverse model. (2) Activity during the execution of imitated actions: The circuit linking F5, PF and STS (solid arrows) may act as a forward model.

of its corresponding inverse model. The appropriate model is selected by generating a responsibility signal based on the sensory prediction of the forward model. The model is extended to consider the context either by using gradient-descent (Wolpert & Kawato, 1998) or by Markovian assumption (HMM) (Haruno et al., 2001). The basic modular architecture was further enhanced to develop a bi-directional higher-level predictive and control model composed of several layers of MOSAIC, called H-MOSAIC (Haruno et al., 2003). H-MOSAIC can learn both elementary movements (low-level motion primitives) and temporal order (high-level sequences) through sensorimotor learning. The lower layer estimates the movement specific motor states, while the higher layers encode the actions.

J. Demiris & Hayes (2002) and Y. Demiris & Johnson (2003) developed a dual route architecture featuring both predictive and learning components for motion imitation in robots. The generative route attempts to generate predictions about the currently observed demonstration using a forward model later compared with actual demonstration. The learning route is activated if a new behavior is observed and adding them into the repertoire. The learning route was implemented with Active Intermodal Matching (AIM) model (Meltzoff & Moore, 1997). According to this model, the mirror neurons are important for synchronization and communication during social interaction. Metta et al. (2006)

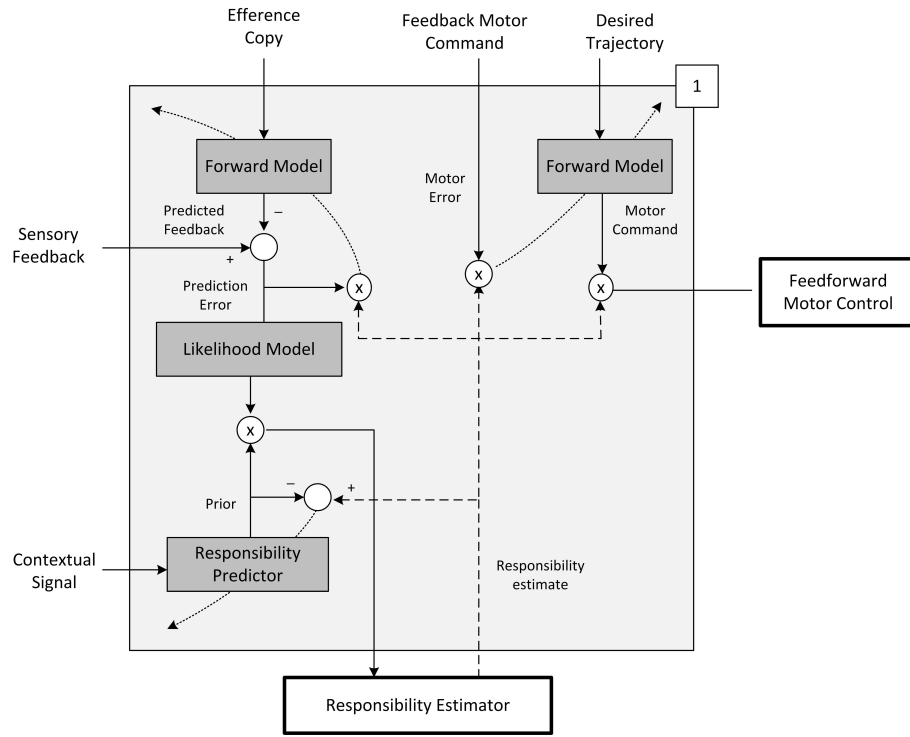


Figure 2.5: A single layer of multiple paired internal model of MOSAIC.

proposed a biologically inspired model of mirror neurons from the perspective of both the imitators and the demonstrator with a unified structure employing the forward model and inverse model.

Hyuk Oh et al. [104] have presented a mirror neuron system based on internal model concepts. This system explicitly model the intra-parietal sulcus and the superior parietal lobe in implementing the function of a frame of reference transformation (FORT system) during imitation (Figure 2.6). The observed actions are encoded into the kinematic visual information in the primary visual cortex (V1) which is transferred to the superior temporal sulcus (STS) and the IPS/SPL. Afterwards, the STS provided the representation of the familiar biological motion and corresponding limbs, while, the IPL/SPL transforms the observed information in the viewpoint of the imitator's intrinsic coordinate system. The two separate radial basis function networks serve as both FORT and adaptive inverse model system with assumption that forward model is known a priori. The FORT system makes the imitator perceive both other and own actions in a common frame of reference.

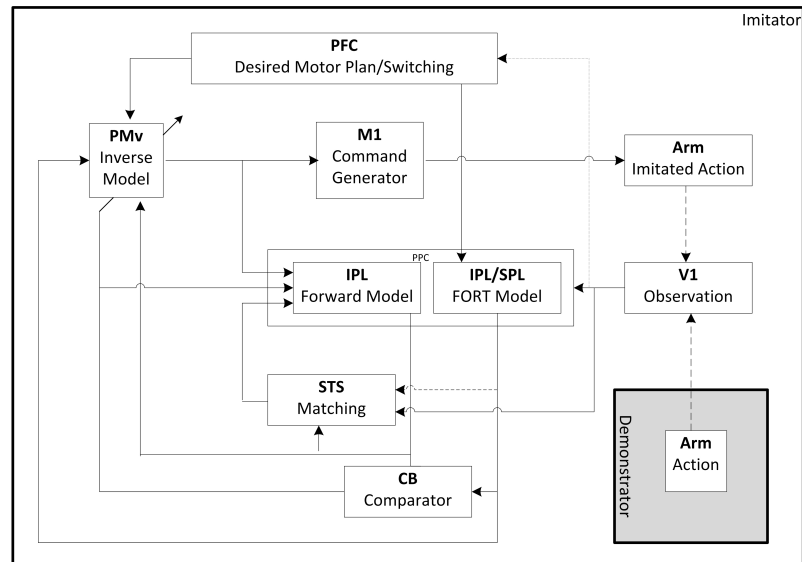


Figure 2.6: Internal model based model of mirror neuron system for learning by imitation for reaching action. The proposed pathway from the IPS/SPL to the STS is represented with the dashed grey line. The dark grey boxes (PFC, PMv, IPS/SPL, and CB) are currently implemented.

The mental state inference (MSI) model (Oztop et al., 2005) was developed to infer the mental state of the demonstrator in term of goals and intentions during grasping movement. The model is based on the visual feedback involving parietal and premotor cortex for generating motion. For processing the goal-directed movements, the visual features of the action extracted by parietal cortex are passed on to the premotor cortex. The premotor cortex calculates the motor signals corresponding to the parietal cortex features. This information is matched with the desired change computed by the prefrontal cortex and relayed to the primary motor cortex and the spinal cord for execution of action. The mirror neuron circuit implements the forward prediction model for estimating the sensory commands based on the input motor code. This prediction measure is used to update the actor's motor commands (simulated movement) based on the observed action (real movement). Another role of forward model in MSI during observation is in inferring the mental state of the demonstrator by creating an imaginary parietal signals. Many possible mental states of an actor are modelled as discrete entities generating a set of predicted sensory signals; therefore, a mental state search mechanism is implemented to find the

best matching state.

The internal models provides a predictive framework for mirror neurons. The implementation of these systems is different but in all these systems the forward-inverse model pairs are activated while performing a task and when the robot receives the input from the demonstrator. The predictions of the forward models are compared to the next state of the demonstrator and the error is used to select the appropriate action for imitation. The error measure provides a confidence in hypothesis given perceived input. The mental state inference (MSI) model (Oztop et al., 2005) hypothesized that forward models are implemented in mirror neurons involved in prediction of goal-directed movement of hand which are activated for mental simulation using visual inputs.

2.2.2 Distributed Dynamic Model

Erlhagen et al. (2006) have presented a Hebbian learning based dynamic model to demonstrate the functionality of various parts of the brain (frontal, temporal and parietal cortex) involved in action understanding during the goal-directed imitation. It has been assumed that the task relevant information in each model layer of the distributed network is encoded by means of sustained activity in local pools of neurons. Another assumption is that the goal related information is effected by various factors such as sensory evidence task information and prior probabilities (Gold & Shadlen, 2002). This architecture proposed that the synaptic links of area PF to the representations in prefrontal cortex may develop using Hebbian learning architecture as suggested by Keyzers & Perrett (2004). Separate neuronal layers encode motion primitives for action perception and action execution. For modelling the areas STS–PF and the PF–F5, connections are reciprocal allowing the flow of information from action observation to action execution and vice versa.

In this model, simulation and action understanding are integrated within a continuous dynamic process. Accordingly, information about the movement and the goal of the

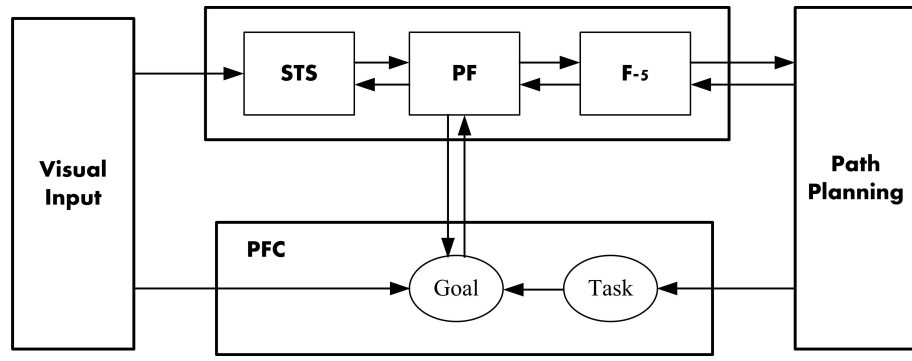


Figure 2.7: Schematic view of the distributed dynamic model architecture (Erlhagen et al., 2006)

movement are represented as dynamic activity in layered neural networks. One part of the model consists of the premotor-parietal-STS mirror circuitry responsible for action observation and action execution. This circuitry is interconnected with a layer in pre-frontal cortex (PFC) that is proposed to encode the intentional action goal framed by the context in which the action is set. In this model the mirror circuitry performs the matching of observed actions with the existing motor repertoire. The PFC, on the other hand, acts as the 'goal layer' and encodes the goal of the observed action.

2.3 Imitation Models - Temporal Sensorimotor Learning

2.3.1 Connectionist Model of Imitation

The connectionist model proposed by Tani et al. (2004) performs learning and sequence generation through Recurrent Neural Network with Parametric Biases (RNNPB). In this work, the concept of mirroring is referred as the movements on trajectory level not actions involving objects. The RNN provides a mapping between the spatio-temporal patterns and the parametric bias (PB) vectors. The model operates in three modes: learning, recognition and generation. During the learning phase, PB vectors, which encode multiple demonstrated movement patterns, are assigned differently for each behavior pattern with a synaptic weight common to all patterns. In recognition mode, the network predicts the sequence of motor values and the sensor values. This error is back propagated for

updating the synaptic weights and PB vectors. After learning, the motion sequences are generated by means of forward dynamics of RNNPB with fixed PB vectors. In a closed-loop mode of RNNPB, the sensory-motor prediction outputs are fed back as input. In action recognition phase, the sensory inputs predict the next vectors by employing the calculated PB vectors. The prediction error is back propagated to the PB units and the current PB vectors are updated by reducing the error. The computation of the PB vectors is conducted by using the regression window of the immediate past steps so that the PB vectors can be modulated smoothly over the window. In the generation mode, the network is assigned a PB vector and is expected to generate the corresponding, previously learned sequence.

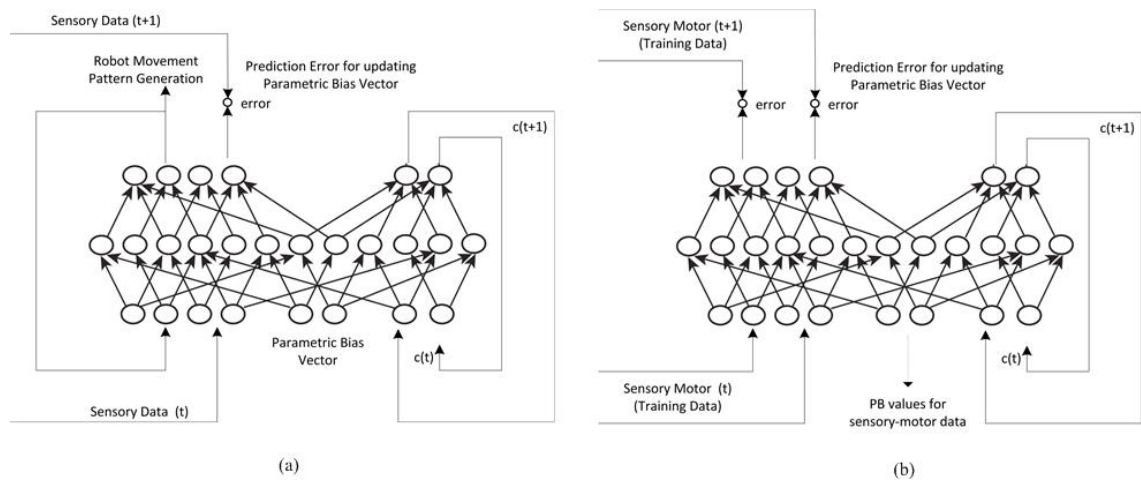


Figure 2.8: (a) RNNPB learning phase: The weights and PB vectors are updated to reduce prediction error, (b) RNNPB interaction phase: the network generates a sensory-motor sequence given a fixed PB vector, while during behaviour recognition the prediction error is used to compute the PB vector corresponding to the sensory input data.

The RNNPB model (Tani et al., 2004) was implemented only for trajectory level imitation and the interaction dynamics between the arm and object were quite limited. For complex tasks manipulation employing a humanoid robot, dynamical neural network based imitation learning architecture is proposed by Ito et al. (2006). This model utilizes the RNNPB scheme for context switching of object handling from the dynamical system perspective. In the learning phase, sensory-motor patterns of guided behaviors are

embedded in the RNNPB in the form of attractor dynamics, which represents the spatio-temporal structure of the target behavior. Multiple behaviours are learned by switching between the different attractor dynamics. During the interaction phase, the intentional acts of human are included by physically forcing the robot to generate learned patterns. The dynamical relationship between the objects and the body were learned as the memory dynamic structure self-organized in the RNNPB.

The RNNPB model do not attempt to provide a relation of the model to the anatomical regions in the brain, except saying that PB units are analogues to mirror neurons. The PB vectors play the role of mirror neurons for providing a connection between the observed dynamics and the motor generation dynamics. However, the relationship between mirror neurons in F5 and PB vectors is more of a metaphorical nature and PB vectors are more like pointers to the brain areas, which can trigger actions (Rebrová, 2014). During recognition phase, the PB vector values are modulated to adapt to the target pattern and iteratively converges to the learned pattern. The generation and perception are performed synchronously in one neural dynamic system (Ito & Tani, 2004). An interesting issue raised by Tani et al. (2004) regarding the mirror neuron is their response during the situation when undesired or harmful behaviours are perceived. They have proposed a suggestion of a meta-learning concept using RNNPB, where another network of PB learns the safe or unsafe behaviours. However, the neurophysiological studies and experiments still need to be explored.

2.3.2 Developmental Model

Neurophysiological studies show that most of the mirror neurons in macaque monkey fire during the goal-oriented grasping task, whereas some of these neurons will fire whenever a certain action is perceived (Fogassi et al., 2005). Thill et al. (2011) presented a computational model for mirror neurons. The proposed model attempted to model the

development of goal specificity in understanding the actions exploiting the information and context about the target actions. The model is based on the self-organizing map (SOM) epitome with associative network architecture utilizing the principles governing the plasticity of SOM. The system encodes the observed action and the object affordance (limiting the input to only these two parameters). The input to the model is an encoding of observed or executed motor primitives and of the context in which the motion primitive is executed (including, for instance, affordances in the perceived environment). The model is trained on repeated presentations of all combination of motion primitives and contexts. After training, the model can be run on-line by continuously feeding it input vectors. The organization of the map depends on the relative distance between input vectors encoding the contextual information and the relative size of the clusters. The trained maps organise in a fashion remarkably similar to that of parietal mirror neurons (Fogassi et al., 2005). Within the map, different areas encode different action primitives (which could represent motions such as reaching or grasping).

The developmental model based on SOM whose self-organizing feature mimics the mirror system. This model highlight the development of goal-specific neurons that may exist in mirror systems since the mirror neurons only fire when the macaque monkey observed an action performed on target goal. As suggested by the MNS2 system (Bonaiuto et al., 2007) that mirror neurons receives input from, among other areas, the superior temporal sulcus (STS) and the anterior intraparietal area (AIP) and the prefrontal cortex (PFC) which transmits the information about the object affordance and the action by self-execution. Thus, the information reaching these neurons encodes variable abstraction about the action. The system was not implemented on an agent, robot or simulation.

2.3.3 Evolutionary Models

Borenstein & Ruppin (2005) presented a neuronal mechanism of imitation from evo-

lutionary viewpoint. According to this approach, the mechanism of imitation is not only innate but it can evolve and persist. Each agent utilizes a feed-forward neural network as a neuro-controller. These neuro-controllers could sense the state of the world and the action of a demonstrator and generate action. These networks are adaptive, whereby the genotype of each individual encodes not only the initial synaptic weights, but also a Hebbian learning rule and learning rate for each synapse. A fitness value is evaluated to assign the appropriate activating motor neurons to the agent's action based on the state-action mapping. Each new generation is created by randomly selecting agents from the previous generation and allowing them to reproduce. Agents are selected according to their fitness. The agent senses the state of the world (context) and the observed action and generates appropriate motor commands. By setting the values of initial context units, the network operates in recognition and generation mode after training.

Apparently, various neurons in the hidden layer are active both when the agent performs a certain actions and when it observes the demonstrator making a similar action, forming internal mirror neurons analogous to the biological mirror neuron system. The neuron whose activation value is significantly higher for both observation and execution are termed as mirror neurons. The agents are radically disembodied and their simulation was conducted in a less realistic environment. Therefore, the applicability of this model reduces drastically.

2.3.4 Common Coding Paradigm

A Common coding paradigm tool based mirror neuron system model has been developed for the social interaction between demonstrator and an imitator (Barakova, 2007). In Common coding paradigm the actions to be generated are coded in terms of perceivable effects. The three main structures of the mirror neuron system, the ventral premotor cortex (PMv), the inferior parietal lobule (IPL), and the superior temporal sulcus (STS),

are modelled within the oscillatory dynamic neural structures of the partner robot for social interaction. Barakova (2007) designed their model based on the hypothesis that the activation of these brain areas co-occur, thus can be projected in a common representation. Actually, there is more than one representational structure that activated by the same event encountered by the sensory and the motor states. In this bidirectional scheme the sensory signals from the STS neurons have been projected directly to the IPL area through the influence of inhibitory neurons. The motor information is co-activated in the PMv area. The mutual interaction between two robots has been modelled through the self-organizing entertainment of oscillatory neurons. The mirroring function is obtained by the self-organization of synchronized neural firing in two robots that share perceptual space. The model was simulated for following and turn-taking behaviours.

2.3.5 Self-awareness during Imitation

One central question about the mirror neuron concept is what makes the specific difference between the execution and observation of action? i.e., whether I observe a motor act of another individual or whether I perform a motor act on my own. Infants presumably have no matching motor commands of the perceived action because they have never performed that action before (Southgate, 2013). In this case the mirror neurons play a major role in self-development through action understanding. This is done by predicting the motor acts experienced by the infants when it senses others' actions (Southgate, 2013). Infants develop a repertoire of actions either from performing those actions themselves or observing others performing those actions. The mirror neuron system makes us capable of taking someone else's viewpoint.

Nagai et al. (2011) and Kawai et al. (2012) have proposed a computational model for the development of mirror neurons system through self-other correspondence. Their computational model is based on the associative sequence learning (ASL) model (Heyes

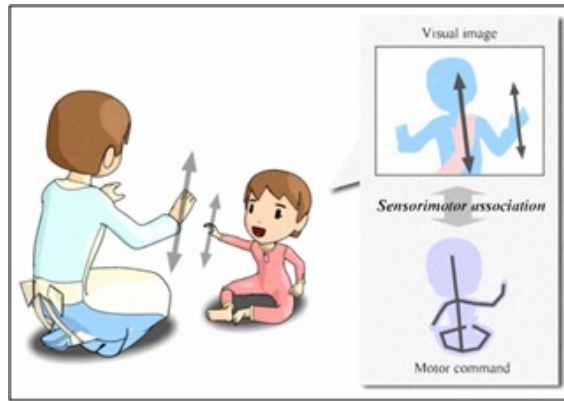


Figure 2.9: An infant learns the association between self-motor commands and observes other's body motions through interaction with a caregiver/parent, which produces the MNS as a by-product of associative learning.

& Bird, 2007; Catmur et al., 2009) which hypothesizes that the correspondence problem between demonstrator and observer can be solved through the sensorimotor experience acquired during development. The computational model relies on the notion Mahler et al. (2008) that the infant's/robot's immature vision, in the early ages, cannot differentiate between the self and other. As vision develops the robot/infant was able to discriminate between self and other actions Nagai et al. (2011). During learning, the robot separately develops two types of associations; first is the self-observation and motor commands of self and the other is the motor commands and other-observation. The system operated by processing visually perceived stimuli through the optical flow detected from robots/infant's vision. The model is divided into two layers: the upper layer consists of vision space containing different actions acquired through the optical flow from vision, while the lower layer consists of motor space containing the motor repertoires. The association between the vision and motor commands is developed through the Hebbian learning. This algorithm was tested on the robot with 6-DOF arm with the assumption that the demonstrator and the imitator have the same repertoire of hand gesture motions. Thus the robot's vision is limited only to hand movements.

Saegusa et al. (2014) describes a developmental framework for action-driven development for the self and action perception. They hypothesised that the observation

of actions can lead to identification of dynamically changing body and its environment. In other words, action generation develops the agent's perception of its own body and actions. The robot develops its perception ability by defining its own body with self-generated actions. This leads to the development of action perception based on observation. The robot develops its body image and motor skills by randomly generating actions through vision and proprioception. Based on the visual motion segmentation, the robot identifies its body from the environment using visuomotor correlation between the self-action and object.

Meltzoff & Moore (1997) present a theoretical model of infant facial imitation based on 'active intermodal mapping' (AIM). AIM puts forward an intermodal mechanism for imitation states that human infants code human acts within an innate supramodal system that unifies observation and execution of motor acts. They assert that imitation is a matching-to-target process. The active nature of the matching process is depicted by the proprioceptive feedback loop. This loop enables infants' motor operation to be assessed against the observed target. According to this model, the observed and generated acts are coded within a supramodal framework, which facilitates infants to ascertain equivalences amongst their own actions and the ones they observe (Meltzoff, 2007a; Meltzoff & Moore, 1997).

2.3.6 Probabilistic Model of Imitation

In probabilistic approaches the set of motion trajectories or motion-elements in the motion patterns are encoded in the probabilistic model. These motion-elements represent the features of the motion patterns characterized by joint angles, position of the joints, or angular velocity Inamura et al. (2003); Calinon et al. (2010). The model is trained with multiple examples of demonstrated action and a set of vocabulary of activities representing different classes of behaviors is created. Whenever a robot observes a particular

behaviour, the robot calculates the likelihood of observed motion with its own repertoire of behaviors. If the likelihood value is relatively large enough, then the robot generates the observed pattern, otherwise a new model for the novel behavior is created and stored in the repertoire. For motion generation, (i.e. decoding of motion patterns from the features elements), the output generated from the probabilistic models are transformed into the continuous motion representation (Billard et al., 2006; Inamura et al., 2004; Calinon & Billard, 2008; Ogawara et al., 2002).

Learning by imitation algorithms can be divided into two general categories; mapping function approach and system model approach. The mapping function based algorithms relied on the mapping between the actions and the state of the agent or an object, while in system model based approaches, the dynamics of the environment and its interaction with the agent is modelled into the system. Learning by utilizing mapping function algorithms constitute classification-based and regression based approaches. Classification approaches categorize the input patterns into classes of actions to be stored in the robot's repertoire and the robot generates the output motion accordingly by observing the demonstration. Hidden Markov Model (HMM) (Rabiner, 1989) and its variants, Gaussian Mixture Model (GMM) (Wu, 2005), Dynamic Bayesian Networks (DBN) (Murphy, 2002), and decision trees (Quinlan, 1987) are some common methods used for classification, recognition and generation of behavior patterns.

Bayesian view of mirror neurons and imitation follows the empirical Bayes rule. For action observation, given a prior expectation about the goal of the observed person, their motor commands can be predicted. Given their motor commands the kinematics can be predicted. The inferred goals are updated by minimizing the prediction error between the predicted and inferred motor commands. The same models are used to infer motor commands from observed kinematics produced by others during perceptual inference. In execution, motor commands are optimized by minimizing the difference between pre-

dicted and desired kinematics, under the assumption that the desired goals are known.

Kilner et al. (2007) presented a conceptual model using predictive coding framework for understanding mirror neuron functionality in recognizing the goals of observed actions and inferring the intention of the observed movement. However, no experimental validation of this conceptual model was provided by the authors. Predictive coding (equivalent to empirical Bayesian inference) is based on minimizing prediction error through recurrent or reciprocal interactions among levels of a cortical hierarchy. This generative model uses backward connections to convey the prediction to the lower level where it is compared to the representation to produce a prediction error. This prediction error is then sent back to the higher layer via forward connections to adjust the neuronal representation of the sensory causes. In other words, the model predicts the sensory (visual or proprioceptive) effects from their cause (motor commands) and vice versa.

Similar account have been presented by Metta et al. [95] using a Bayesian interpretation of recognition of actions through visual observation and proposed the models for mirror and canonical neurons. In this interpretation the object affordance are used to identify the most likely sequence to be executed. In this model the difference in the predicted and the observed pattern is accounted for and the inverse model is used for visuo-motor mapping. The object affordance is calculated by counting the occurrences of actions for the objects.

Shon, Storz, & Rao (2007) constructed a real-time imitation system using non-parametric Bayesian inference. Left-to-right HMM (Rabiner, 1989) is employed to encode and recognize the joint positions of the actions executed by the human instructor. The smooth movements are generated by linearly interpolating the joint positions between each HMM. This framework attempts to compute the distribution over possible actions given the current state (of the world); a next predicted state and the desired end state or goal. This distribution is identified with an inverse model and Bayes' rule is used

to compute an estimate of the distribution using forward model predicting how the environment will react to actions taken in the environment. In another work, Shon, Storz, Meltzoff, & Rao (2007) used Bayesian algorithm and Meltzoff and Moore's Active Inter-modal Mapping (AIM) hypothesis for a goal-directed probabilistic learning framework. Bayesian inference is used to decide which actions are most effective.

Inamura et al. (2004) proposed a Mimesis Model based on Hidden Markov Model for motion abstraction and generation using primitive symbols. It is postulated that human movement consists of atomic units called primitives, which are sequenced together and combined to form more complex behavior (Schaal, 1999). They have presented HMM as a bidirectional model of Mirror Neurons. The observed motions are transformed into motion elements determined using joint angles of the observed human body parts. The motion elements are symbolized as Gaussian function (Inamura et al., 2003). HMM is used for presenting a relationship between sequence of motion patterns and the symbols. For motion generation, this system utilizes the same HMM model which is used for motion abstraction to decode primitive symbols for extraction of sequence of motion. Motion is generalized using the state sequence estimation and the transition probabilities. A hierarchical mimesis model is presented in Nakamura et al. (2007); Lee et al. (2010), where the authors have extended the mimesis model capable of interaction with environment to geometric symbol space for communication and interaction between humans and humanoids. The proto-symbol space is constructed using the Kullback-Leibler distance information between two proto-symbols information and the multi-dimensional scaling. In other words, meaning and tendency of behaviors are described as geometric relationship of the space constitution.

Variants of HMM have been used to develop imitation methods. Kulic et al. (2007b) developed a human motion recognition and imitation method based on Factorial Hidden Markov Model (FHMM) (Ghahramani & Jordan, 1997). When using HMM for both mo-

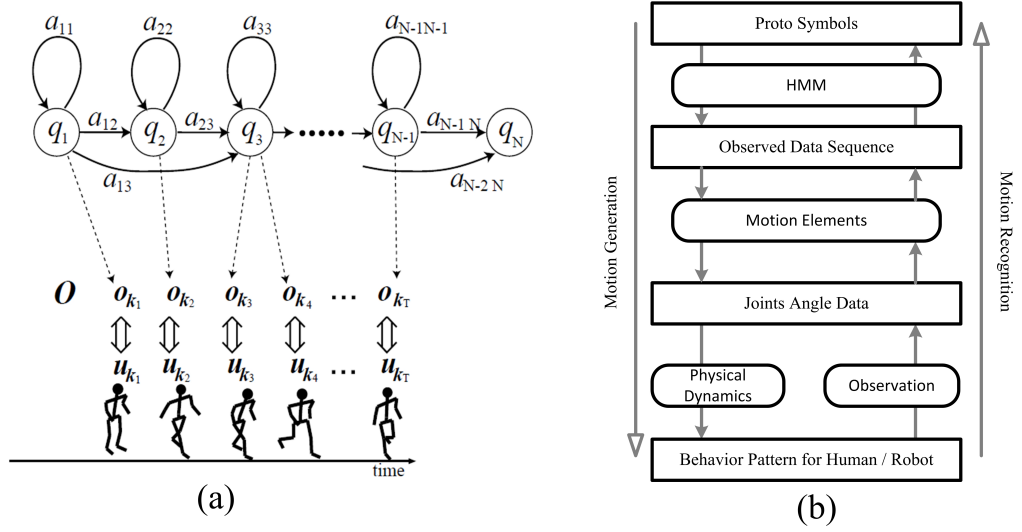


Figure 2.10: Mimesis Model presented by Inamura et al. (2004)

tion recognition and generation, there is a trade-off between recognition and generation performance, in particular when selecting the number of states of the model. FHMM is HMM variant where multiple HMM chains are used to generate independent output. Each dynamic chain in FHMM models the observed motion pattern with its own transition and output probability parameters. At each time step, the output generated by each chain is added together to generate the optimized observed output. Similar to the mimesis model, a symbol space is constructed to discriminate between behavior patterns. For motion generation, a greedy policy estimate is used for the state transition matrix. Due to the higher number of states available to represent the motion, FHMMs achieve better spatial accuracy compared to a single chain HMM model.

2.3.7 Sensorimotor Associative Learning Architectures

The property of the associative network architecture is its ability to retrieve a stored pattern based on the input provided. The idea was derived from the physiological plausible connection between the brain regions using Hebbian learning rule (Keyzers & Perrett, 2004). It was hypothesized that mirror neurons follow a similar mechanism (Oztop et al., 2006): when the organism generates motor commands the representation of this command and the corresponding sensory data are associated within the mirror neuron

system. When the similar stimuli (auditory or visual) are presented, the associated motor commands are recalled automatically. Neural network based representations have been developed to computationally model this property. In associative memory models, various input modalities (somatosensory, visual and auditory) are associated with the motor commands of the generated action.

Chaminade et al. (2008) have presented a neural network based Hebbian-like learning of sensory-motor associations resulting from self-observation implemented on a robotic hand. The proposed model states that imitation can emerge from intrinsic properties of a neural associative network during motor babbling. The visuomotor association created by combining retina and motor inputs form an input pattern is stored in the higher order Hopfield (HHOP) (Oztop et al., 2008) network to deal with correlated pattern. The associate memory is based on Hebbian-like learning mechanism with units resembling neurons.

Similarly, Elshaw et al. (2004) and Wermter et al. (2004) provides a hierarchical multimodal learning architecture for robot learning by imitation that used language, vision and motor actions as inputs. The model develops an association between motor commands and high-level vision inputs using Helmholtz Machine (HM) based learning (Dayan, 2000). Using sparse coding approach the HM creates edge detectors from images and produces the generative model of the data as neural connections (Elshaw et al., 2005). The Helmholtz machine area (the first layer) is directly linked to the motor output and identifiable groups of neurons specific motor units Figure 2.11. After learning, the robot recognizes the observed behavior and reproduces the same action based on the visual stimuli.

Kuniyoshi et al. (2003) have developed a visuo-motor neural learning system based on orientation selective visual movement and a high-dimensional temporal sequence learning mechanism. For the sensory-motor interface, a spatiotemporal pattern memory neural

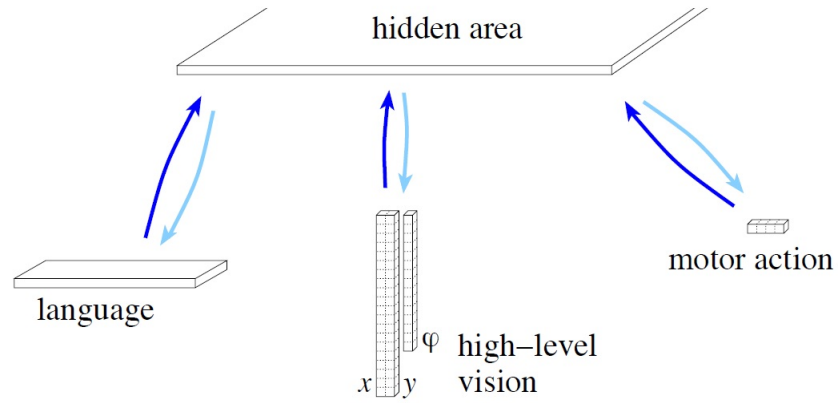


Figure 2.11: Multimodal learning achitecture developed by Elshaw et al. (2004)

network was used as associative memory for the generation of arm movement of a robot. This neural structure is also called non-monotonic dynamic neural network. Billard & Hayes (1999) have presented a model using Dynamic Recurrent Associative Memory Architecture (also known as DRAMA) for learning of sequential data. The model consists of time-delayed fully recurrent neural network without hidden units using Hebbian update rules. Complete architecture is shown in Figure 2.12. The demonstrator's joints Cartesian coordinates are provided as input to the temporal cortex (TC) which is transformed into egocentric coordinates. The motor control is modelled in a hierarchical structure with spinal cord module made of motor neurons and inter-neurons and the primary cortices (M1) module monitoring the activation of spinal networks. The premotor cortices and cerebellum module are invoked during learning of movement implemented using associative memory.

Based on the Recurrent Neural Network with Parametric Bias (RNNPB) architecture for mirror neurons, Ogata et al. (2005) have presented a multi-modal architecture using RNNPB by extracting audio, visual and tactile information from different sensors attached to a robot. The architecture is based on forward prediction model using current state as input and predicting next sensory state as output. Sugita (2005) have extended the RNNPB model to present a connectionist model for acquiring the semantics of a sim-

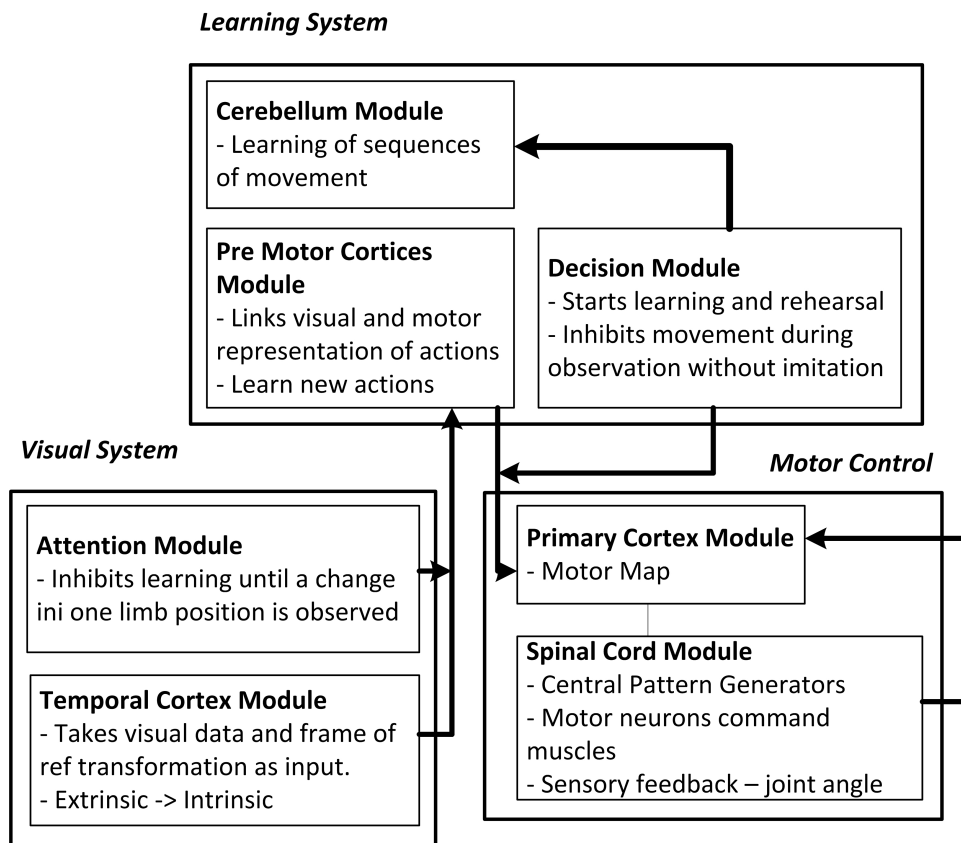


Figure 2.12: The model developed by Billard & Hayes (1999) consists of seven modules which give an abstract and high-level representation of corresponding brain areas involved in visuo-motor processing. The seven modules are: the attention and TC modules, the primary motor cortex and spinal cord modules, the PM cortex and cerebellum module, and the decision module.

ple language through the behavioral experiences of a real robot. The model is composed of two recurrent neural networks with parametric bias (RNNPB), one for the linguistic module and one for the behavioral module. The linguistic module learns to recognize a set of sentences, represented by a sequence of words, while behavioral module learns a set of sensory-motor sequences. This model generates word sequences or sensory-motor sequences condition to forward models. After training, the robot was able to generate behavior corresponding to the learned sentences. The connection between the language and the behavior situated in the sensory-motor cortex is provided by self-organizing through iterative interactions between the two modules.

Table 2.1: A summary table for models discussed enlisting the properties and architecture of these models

Model	Imitation	Motor Control	Neural Modelling	Summary
MNS-1			✓	Mirror's ability to relate the self-observation to action recognition.
MNS-2			✓	Audio-visual mirror neurons through use of dynamic memories for hand and object affordance.
Chain Model	✓		✓	Motor and mirror neurons are organized in action goal-specific neural chains. Activation is done by propagation through specific chain.
Sensorimotor Processing Model		✓		Sensory-motor loop enabling the use of mirror-coded motor information. Motor info. is used for visual processing.
MOSAIC		✓		Modular architecture with multiple pairs of forward and inverse models.
Demiris Model Metta et al.	✓ ✓	✓ ✓		Dual route architecture based on forward models. MN modelled based on internal model. Imitator consider themselves in the position of demonstrator.
FORT Model	✓		✓	Frame of reference transformation and adaptive inverse model. Imitator perceives both other and own actions in common frame of reference.
MSI Model	✓	✓		Forward models implemented in MN for prediction of goal-directed actions activated for mental simulation using visual inputs.
Distributed Dynamic Model	✓		✓	Distributed neuronal network for action understanding and goal-directed imitation as a continuous dynamic process.
Simulation Theory			✓	Emotion reading by recursive body loop and Hebbian learning for mirroring functions.

Table 2.1: A summary table for models discussed enlisting the properties and architecture of these models

Model	Imitation	Motor Control	Neural Modelling	Summary
Connectionist Model - RNNPB	✓			Parametric Bias vectors provides connection between visual and motor dynamics.
Developmental Model			✓	Based on SOM architecture for development of goal specific mirror neurons.
Evolutionary Model	✓			Evolutionary viewpoint of imitation i.e. imitation is not only innate but evolves and persists.
Common Coding Paradigm	✓			Interacting agents share perceptual space, the common representation for perception and action. Actions are encoded in terms of perceivable effects.
Multimodal Architecture	✓			MNs acquire sensorimotor properties whenever individual experience a contingency between seeing and doing.
Self-Awareness Models	✓	✓		the other acts like me and I can acts like the other.
Bayesian Models	✓			Given a prior expectation about the goal of the observed action, motor commands can be predicted.
Hidden Markov Model	✓			Motion encoding/learning and execution using HMM.

2.4 Summary

The discovery of mirror neurons is a major development in the field of robotics and neuroscience. Mirror neurons exemplify the association between perception and motor action. The functional characteristics of mirror neurons led to the development of robotic systems with advanced motor, perceptual, and cognitive capabilities. The most significant feature is the perceptual activation of mirror neurons that imparts a simple mechanism for mental simulation of the observed behaviour, which leads to its understanding. The computational models summarized in this chapter are related to the cognitive ability of mirror neurons in action understanding, imitation and mental simulation. The models discussed either model the system as neural mechanism of mirror neurons in robots that support imitation or they assume the existence of mirror neurons and develop a learning system supporting imitation. Some of these models encode either motor information or goal-directed information or make use of both.

In robotic view of imitation learning, the intentional understanding mechanism of mirror neuron is implemented using predicting or anticipating relevant actions/goals or sensory signals. The forward and inverse models of imitation extend the concept of mirror neurons in attempts to understand motor learning and associate the mirror neuron activation with the forward and inverse models. The predictive capability of the forward models during physical events assists in useful manipulatory actions coupled with the inverse models to generate the effects of one's own actions. The associative memory hypothesis of mirror neurons described by Hebbian learning are computationally plausible, however, According to Cooper et al. (2013), the associative model perspective for development of mirror neuron system was not limited to Hebbian learning for automatic imitation. The associative learning plays a crucial role in the development of mirror neurons system. The probabilistic models of imitation do not simulate any brain area; however,

these models are inspired from the mirror neuron functionalities and focused on its motor control abilities.

For action recognition and understanding, the function of STS has not yet been utterly apprehended. Neurons in STS provide an abstract, viewer-independent representation that might clarify the link to the motor representations (Perrett et al., 1991). These STS cells encode information in object-centred instead of viewer-centred frame of reference (Olson, 2003). It has been suggested that neurons responsive to multiple views of an action or object could be established by integrating the outputs of various view-sensitive cells adjusted to multiple views of an action or object, which is also plausible from the modelling point of view (Perrett et al., 1991; Hasselmo et al., 1989).

The mechanism for processing of information for view-invariant representation in STS still needs to be determined: whether it simply incorporate a bottom-up ventral pathway (Knott, 2012), or it inevitably requires motor information mediated by the parietal area (Perrett et al., 1991). Following the suggestions of Farkaš et al. (2011), I argue that STS is involved in action recognition without requiring the motor component. Indeed, humans are able to recognise a wide variety of actions, even though some of these cannot be mapped to their own motor repertoire. This thesis points out the view that action recognition may be achieved by visual inspection of the patterns.

Most computational models learn to connect motor and perceptual representation; however, a critical assumption in these models is the dependency on the accessibility of invariant perceptual representations in STS which are then linked to the motor information. In other words, these models process the perceptual and motor representations assuming that both are first separately incorporated in time and then associated in one-to-one fashion (Keysers & Perrett, 2004). However, I contend that the process of acquisition of viewer-independent action representations should be a part of the model.

CHAPTER 3 – DEVELOPMENTAL MODEL OF IMITATION LEARNING THROUGH SELF-EXPLORATION

In order to imitate an observed behaviour, the observer has to recognize the action, but in order to recognize the actions the observer must be able to perform the action (Cuijpers et al., 2006). This task can be achieved by viewing the development as the incremental process: infants learn new ability on top of the abilities already present (Pfeifer et al., 2007). Motor babbling or body babbling is a process of learning how specific muscle movements achieve various elementary body configurations (Rao et al., 2004). Body babbling has been described as behaviour for self-exploration adopted by infants which helps them to learn a set of motion primitives that could be used as a basis for imitation learning (Bandera et al., 2007). It is considered essential for the development of more complex behaviours, self-awareness and social interaction skills. Through the babbling process, the infants or robots comprehend an observed action as they compare the observed behaviour with motion primitives they have stored in their memory.

3.1 System Overview

Self-learning or self-imitation requires a mapping that associates an observed self-motion with the corresponding motor command. Sensory-motor learning through motor babbling has been demonstrated to be efficacious for autonomous humanoid robots in developing an associative relationship amongst self and the surrounding environment (Jansen et al., 2004; Saegusa et al., 2009; Baranes & Oudeyer, 2013). In this thesis, I have implemented a simple method for self-recognition on humanoid robot through the use of mirror image. During this stage, the robot generates random movements of the body and associates the action produced by the self with its effects perceived through vision. The visual space consists of its own body image seen in a mirror. To make imitation

learning practicable, the observer ought to have an apprehension of its own primitive motor skills (proprioception), observe demonstrations and their consequences, and translate them within the context of its own primitives. In doing so, the robot builds up novel motor skills by developing the combinations of primitives.

The proposed MNS model is designed to permit the robot to associate the perceived self-performed action with actions in its own (self) motor repertoire empowering it to understand the perceived movement by taking into account the view-dependency of neurons. The outline of the MNS model is presented in Figure 3.1. The proposed model is inspired from the mirror neuron model presented by Rebrova et al. (2013). The mirror neurons represented by the area F5 are connected with representation in STSp. Area PF forms a layer of neurons in associative network while the AIP pathway is represented by F5-to-STSa part of the model. The low level motor and visual information are processed through TGARM and Inc-KSFA, and form a high level representation of movements in F5 and STSp.

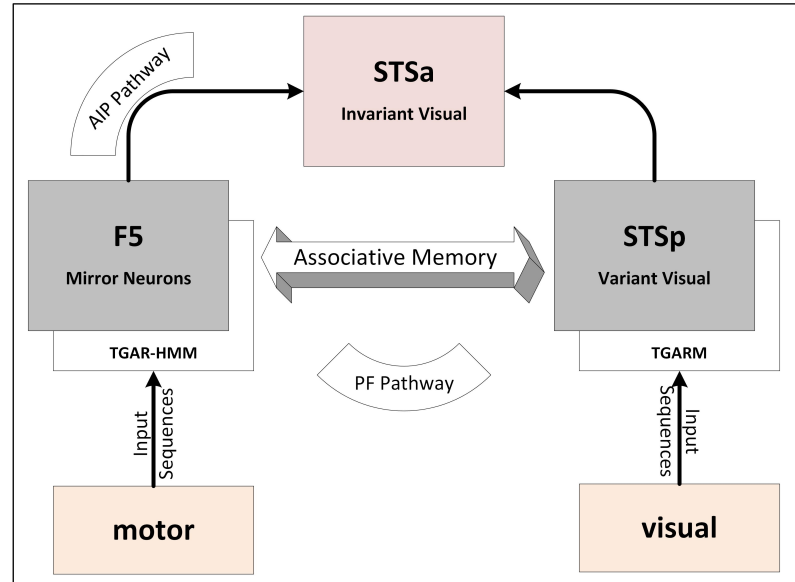


Figure 3.1: Mirror Neuron Model (Adapted from (Rebrova et al. 2013)).

The pathway F5-PF-STSp develops an associative link between invariant motor information from F5 module with variant perceptual information in STSp via the pari-

etal area (PF). This pathway is modelled through the Topological Gaussian Adaptive Resonance Associative Memory (TGAR-AM). In the learning process the network first forms mapping from each motor representation onto visual representation from the self-exploratory perspective. Afterwards, the representation of the motor commands is associated with all possible visual perspectives. This association is developed in order to activate the appropriate motor commands utilizing the visual stimuli. The second part of our model is the F5-AIP-STSa pathway, which links the mirror neurons in F5 with invariant representations in STSa.

The learning system begins with determining the atomic motor commands from continuous movements, defined as motion primitives. In order to effectively imitate others, the observer must be able to recognize its own primitive actions from visual data. To formulate an apprehension of its own actions, the observer begins by gathering visual perception of its own primitive actions using the mirror image reflection. By performing random actions in front of the mirror generating a mapping between the generated motor commands and the consequent perceived visual changes. This process consisting of self-learning or self-exploration through mirror image perception is called body babbling. Figure 3.2 shows the proposed system.

The vision frames acquired while the humanoid robot performs actions in front of the mirror are translated into feature vectors using proposed Incremental Kernel Slow Feature Analysis. These vectors represent the slowly varying features. The change among these feature vector values is utilized to determine the unsupervised episodic segmentation defining the start and end of the action. These segmented boundaries of action assists the robot to group the observed own actions as primitive actions. A segment is thus an atomic piece of a demonstrated action. Clustering is referred to as partition of different actions into disjoint groups. Once the start and end of different actions are determined by Incremental Kernel SFA (Inc-KSFA), the motion patterns are clustered together. These

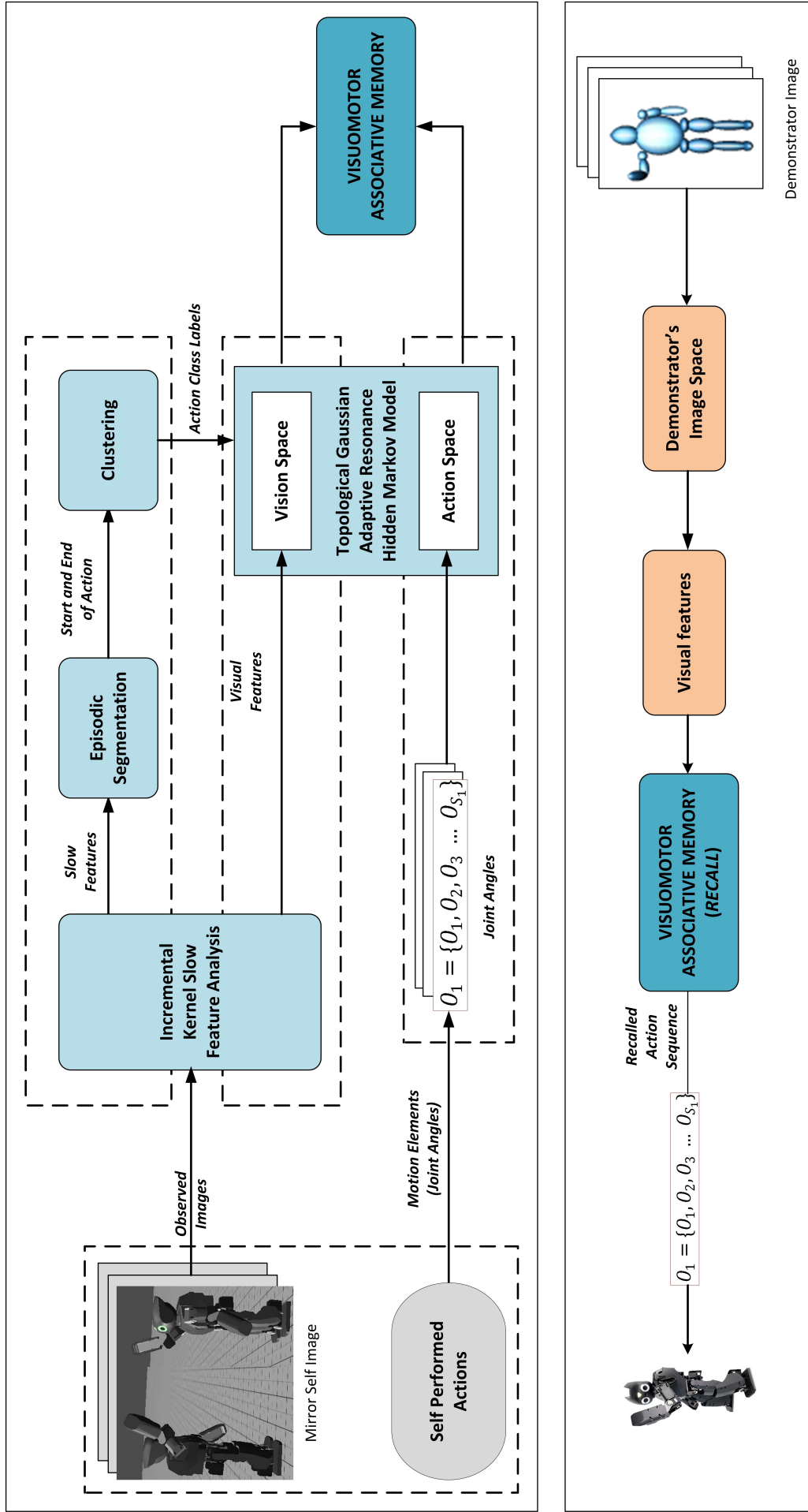


Figure 3.2: Architecture for imitation learning through self-exploration.

clusters are labelled and stored into the memory of robot.

Appropriate "motion elements" must be learned during imitation process because these elements forms the fundamental constituents for behaviour recognition and generation (Inamura et al., 2003). During the implementation of the proposed architecture, in addition to obtaining the visual images of self-performed actions, the joint angle values for different behavioural actions are also acquired as motion elements. These motion elements represented through joint angles are mapped onto the behaviour space. For learning the motion features I developed a probabilistic incremental learning algorithm called Topological Gaussian Adaptive Resonance Hidden Markov Model (TGAR-HMM). In conventional HMM, defining the appropriate number of states in the model is difficult (for incremental learning) in order to avoid computational underflow or overflow. In contrast, the developed algorithm is based on incrementally learning spatio-temporal behavioural sequences by developing the graph based structure of the observed patterns in the form of topological map. The topological model incrementally defines the number of states required by the probabilistic model to encode the observed motion elements.

In addition to the episodic segmentation, the output of Inc-KSFA serves another major function. Based on the segmented data, the learning algorithm is triggered; whenever an action starts, the learning algorithm incrementally encodes the motion elements (joint angle values). Similarly, as the action ends, the robot stops learning that particular action. The learned motion elements are also labelled using the clusters defined Incremental Kernel Slow Feature Analysis.

After generation of these maps independently, the visual space and the behaviour space are connected based on associative memory. In addition to the construction of behaviour space through TGAR-HMM utilizing motion elements, a visual space is developed through TGAR-HMM utilizing the visual image features acquired using Inc-KSFA. In order to develop an association between the observed visual features (visual space) and

self-motor actions (behaviour space), I developed an incremental associative memory architecture using Topological Gaussian Adaptive Resonance Associative Memory. The pathway F5-PF-STSp organizes an associative link between invariant motor information from F5 module with variant perceptual information in STSp via the parietal area (PF). This pathway is designed by the TGAR-AM. In the learning process the network first forms mapping from motor representation onto corresponding visual representation from the self-exploratory perspective. Afterwards, the same representation of the motor commands is learned to be associated with all possible visual perspectives of that particular action. This association is developed in order to activate the appropriate motor commands utilizing the visual stimuli. The second part of our model is the F5-AIP-STSa pathway, which links the mirror neurons in F5 with invariant representations in STSa.

Once the association is developed and learning is completed, we assume that a partner robot comes before the robot performing the similar actions from various perspectives as previously learned by the robot. Based on the sensorimotor association, the robot recalls the corresponding motor commands from the memory developed during body babbling and performs the actions. Then, if the robot observed an action from various perspectives, the motor representation of the action is triggered.

Behavioural actions are learned by the combination of various motion primitives to generate complex actions based on their observations (Billard & Matarić, 2000; Nicolescu & Mataric, 2003). Similarly, in our work, a new behaviour is created from a combination of two or more motion primitives learned during self-exploration. The combination is done by recalling the similar actions from the associative memory. For example, the complex action of clapping consists of recalling the motion primitive of raising the arm followed by the primitive lowering the arm in a sequentially continuous manner. If the observed behaviour is not present in the robot's memory (i.e., if there is no associative link available to the demonstrated action in memory) the learning mechanism is invoked

and the newly observed action is learned by the robot.

3.2 Summary

This chapter provides an overview of the proposed mirror neuron system which connects the motor representations (F5) with the visual representations (STS). The architecture is inspired by the empirical discovery stating that in F5 as well as STS, majority of the neurons are view-dependent. I presented a developmental framework for humanoid robot learning that is able to learn by imitation through self-exploration. The purpose of self-exploration presented in the experiments is to enhance the robot's knowledge and to develop its motor control ability. The robot first learns about its own body gathering all information by self-exploration through body babbling. The proposed model can be considered as the developmental step towards allowing robots to systematically learn how to integrate perception and action through self-experiences much like a human being does, so as to generate adaptive behaviours efficiently and flexibly.

CHAPTER 4 – EPISODIC UNSUPERVISED SEGMENTATION

In this thesis, automatic temporal episodic segmentation of observed actions is performed based on the image sequences captured from the robot’s on-board vision sensors. The observed actions are segmented into episodes of different actions determined by the start and end of actions. For this purpose, I have developed an algorithm called Incremental Kernel Slow Feature Analysis (Inc-KSFA) algorithm. Inc-KSFA extracts slowly varying features from rapidly changing raw input signals. The variation of slowly changing features is exploited to determine the occurrence of different activities incrementally from individual data points of single data stream. The decision about segmenting the sequence is based on the change in the slowly varying features. The output of the Incremental Kernel SFA serves two major functions. Firstly, based on segmented data the learning algorithm is triggered. Every time an activity starts, the learning algorithm incrementally encodes the joint angle values. As the action ends (defined by the segmentation algorithm), the robot stops learning. Secondly, based on the start and end of the action, the robot makes clusters of the learned actions. These clusters are labelled and stored in the robot’s memory.

4.1 Slow Feature Analysis: Formulation

The Slow Feature Analysis (SFA) is a technique that extracts slowly varying features from raw input stream of sensory signals (Wiskott & Sejnowski, 2002). The main intuition behind SFA is based on the principle that the information (e.g. actions or activities) contained in a signal (e.g. images or video) do not change suddenly, but slowly over time (Wiskott & Sejnowski, 2002). In other words, the slowness learning principle represents the salient features on an input stream of data in a way invariant to frequent transformations. SFA is originally designed to learn invariances from the model of a primates’ visual

system. Several studies have been conducted to show the relevance of slowness principle to the biological sensory cortex for learning of place-cells and spatial view cells from high-dimensional visual input (Franzius et al., 2007; Berkes & Wiskott, 2005). SFA have been widely used in various machine learning applications such as classification (Berkes & Wiskott, 2005; Kuhn et al., 2011), feature extraction (Zhang & Tao, 2012), data segmentation (Nater et al., 2011), invariant object recognition (Berkes & Wiskott, 2005) and dimensionality reduction (Kompella et al., 2012).

Slow Feature Analysis (SFA) is an unsupervised approach which searches for a set of mappings $\mathbf{g}(x) = [g_1(x), \dots, g_J(x)]^T$ from I -dimensional input data $\mathbf{x}(t) = [x_1(t), \dots, x_I(t)]^T$ to generate J -dimensional output signal $\mathbf{y}(t) = [y_1(t), \dots, y_J(t)]^T$ with components $y_j(t) := g_j(x(t))$ such that $j \in \{1, \dots, J\}$ and $i \in \{1, \dots, I\}$. The optimization problem of SFA is defined by minimizing the temporal variations of the output signal (Figure 4.1):

$$\Delta(y_j) := \langle \dot{y}_j^2 \rangle_t \quad \text{is minimal} \quad (4.1)$$

Under the constraints:

$$\langle y_j \rangle_t = 0 \quad (\text{Zero Mean}) \quad (4.2)$$

$$\langle y_j^2 \rangle_t = 1 \quad (\text{Unit Variance}) \quad (4.3)$$

$$\forall i < j, \langle y_i y_j \rangle_t = 0 \quad (\text{Decorrelation}) \quad (4.4)$$

where $\langle y \rangle_t$ and \dot{y} represent the temporal averaging and the derivative of y , respectively. The primary objective of the optimization problem is to minimize the temporal variations of the output signal. The temporal variations in a signal (the $\Delta(y_j)$ -value) is the objective of the optimization problem and is measured by the difference between con-

secutive time steps: $\dot{y}_j(\mathbf{x}(t)) = y_j(\mathbf{x}(t)) - y_j(\mathbf{x}(t-1))$ (Nater et al., 2011; Böhmer et al., 2011).

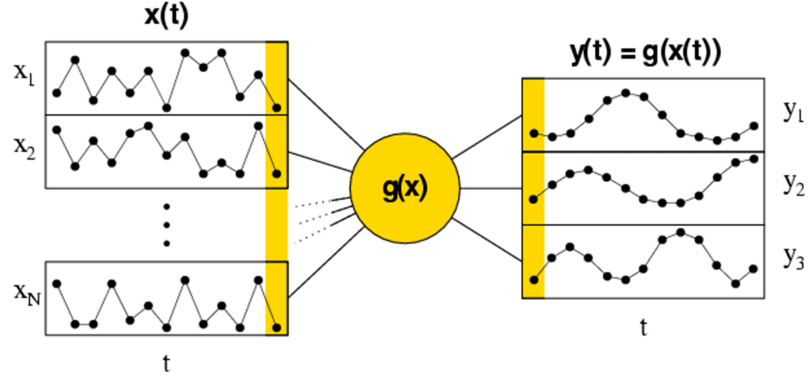


Figure 4.1: Schematics illustration of the optimization problem solved by slow feature analysis (Adapted from Wiskott, 2003). Given an input signal $x(t)$, find an input-output mapping function $g(x)$ that generates an output signal $y(t) = g(x(t))$

The constraints (4.2) – (4.4) are inserted to exclude trivial solution. The unit variance constraint (4.2) and zero mean constraint (4.3) prevents constant signals to emerge and normalize all output signals to a common scale, which makes their temporal derivative directly comparable. The decorrelation constraint (4.4) imposes distinctness among data patterns and requires that the output signals are decorrelated from one another and guarantees that different output signal components code for different information.

Often, the mapping is assumed to be linear such that the input-output transformation is the weighted sum i.e., $g(\mathbf{x}) = \mathbf{w}^T \mathbf{x}(t)$. However, for the real time applications the input signals are not linear. Therefore, the non-linear problem is transformed to a linear one by expanding the input into the space of non-linear functions (Wiskott & Sejnowski, 2002). The non-linear input features are expanded through expansion function, $h(\cdot)$, such that $\mathbf{z}(t) := h(\mathbf{x}(t))$, yields the non-linearly expanded signal. After expansion, the problem can be treated as linear and the j -th output signal component is given by:

$$y_j(t) = g_j(\mathbf{x}(t)) = \mathbf{w}_j^T \mathbf{h}(\mathbf{x}(t)) = \mathbf{w}_j^T \mathbf{z}(t) \quad (4.5)$$

Generally, the expanded signal may not have zero mean, however, without the loss

of generality, the centred data matrix is computed by subtracting the mean over time such that $\mathbf{z} := \mathbf{h}(\mathbf{x}) - \mathbf{h}_0$, where $\mathbf{h}_0 = \langle \mathbf{h}(\mathbf{x}(t)) \rangle$. Based on this, the input-output function can be obtained through:

$$y_j(t) = g_j(\mathbf{x}) = \mathbf{w}_j^T \mathbf{z}(t) = \mathbf{w}_j^T (\mathbf{h}(\mathbf{x}) - \mathbf{h}_0) \quad (4.6)$$

Assuming that the signal has unit variance such that $\mathbf{w}_j^T \langle \mathbf{z}\mathbf{z}^T \rangle_t \mathbf{w}_j = 1$, where $\mathbf{z}\mathbf{z}^T = \mathbf{I}$, the optimization problem is treated as:

$$\langle \dot{y}_j^2 \rangle_t = \mathbf{w}_j^T \langle \dot{\mathbf{z}}\dot{\mathbf{z}}^T \rangle_t \mathbf{w}_j \quad (4.7)$$

and

$$\langle y_i y_j \rangle_t = \mathbf{w}_j^T \langle \mathbf{z}\mathbf{z}^T \rangle_t \mathbf{w}_j \quad (4.8)$$

The optimization problem can be written in more convenient way using matrix notations:

$$\min_{\mathbf{W}} tr(\mathbf{W}^T \dot{\mathbf{Z}}\dot{\mathbf{Z}}^T \mathbf{W}), \quad \text{s.t.} \quad \mathbf{W}^T \mathbf{Z}\mathbf{Z}^T \mathbf{W} = \mathbf{I} \quad (4.9)$$

where $\mathbf{Z} = [\mathbf{z}_1, \dots, \mathbf{z}_n]$ contains the input features and $\dot{\mathbf{Z}}$ represents the temporal derivation matrix, and $tr(\cdot)$ computes the trace of a matrix.

In the first step, the technique of whitening matrix is applied to obtain the projection which whitens the matrix, as will be explained below. The matrix \mathbf{S} represents the whitening matrix to fulfil the unit variance constraint such that $\mathbf{S}^T \mathbf{Z}\mathbf{Z}^T \mathbf{S} = \mathbf{I}$. Then, the directions of least variance in the derivative signals $\dot{\mathbf{Z}}$ are found on the derivative covariance matrix $\dot{\mathbf{Z}}\dot{\mathbf{Z}}^T$ and represented by an orthogonal matrix \mathbf{R} to obtain the projection $\mathbf{W} = \mathbf{S}\mathbf{R}$

which solves (4.9). Then SFA can be represented as:

$$\min_{\mathbf{R}} tr(\mathbf{R}^T \mathbf{S}^T \dot{\mathbf{Z}} \dot{\mathbf{Z}}^T \mathbf{S} \mathbf{R}), \quad \text{s.t.} \quad \mathbf{R}^T \mathbf{S}^T \mathbf{Z} \mathbf{Z}^T \mathbf{S} \mathbf{R} = \mathbf{I} \quad (4.10)$$

The temporal derivatives are computed using:

$$\dot{\mathbf{Z}} = [\mathbf{z}_2, \dots, \mathbf{z}_n] - [\mathbf{z}_1, \dots, \mathbf{z}_{n-1}] = \mathbf{Z} \mathbf{P}_n \quad (4.11)$$

where \mathbf{P}_n is a $n \times (n-1)$ matrix with the elements $\mathbf{P}_n(i, i) = -1$ and $\mathbf{P}_n(i+1, i) = 1$.

The zero mean constraint can be obtained by computing the centred data matrix such that $\bar{\mathbf{Z}} = \mathbf{Z} - \mathbf{1}_{n \times 1} \boldsymbol{\mu}_{\mathbf{Z}}$ where $\boldsymbol{\mu}_{\mathbf{Z}}$ is the mean of the data patterns, and $\mathbf{1}_{a \times b}$ is an $a \times b$ matrix with all elements set to 1. Similarly, in the first step, the technique of whitening transformation is applied to obtain the projection which whitens the matrix and satisfy the unit variance constraint. For this I compute the eigenvalue decomposition of $\bar{\mathbf{Z}}$ as $\bar{\mathbf{Z}}^T \bar{\mathbf{Z}} = \mathbf{Q} \boldsymbol{\Lambda} \mathbf{Q}^T$. For high dimensional data I calculate the Singular Value Decomposition (SVD) (Golub & Loan, 2012) of the centred data matrix $\bar{\mathbf{Z}}$ as:

$$\left[\bar{\mathbf{Z}} \mathbf{Q} \boldsymbol{\Lambda}^{-\frac{1}{2}} \right] \left[\boldsymbol{\Lambda}^{\frac{1}{2}} \right] \left[\mathbf{Q}^T \right] = \mathbf{U} \mathbf{D} \mathbf{V}^T \quad (4.12)$$

I only keep the non-singular dimensions with eigenvalues above a certain threshold.

The projection which whitens the matrix is provided by $\mathbf{S} = \mathbf{U} \mathbf{D}^{-1}$.

In order to find the output of SFA, in the second step, the Eigen Decomposition (ED) of $\dot{\mathbf{Z}} \dot{\mathbf{Z}}^T$ is computed such that $\mathbf{S}^T \dot{\mathbf{Z}} \dot{\mathbf{Z}}^T \mathbf{S} = \mathbf{R} \mathbf{H} \mathbf{R}^T$. Here $\dot{\mathbf{Z}}$ represents the centred derivative data matrix computed by subtracting $\bar{\mathbf{Z}}$ from its mean $\boldsymbol{\mu}_{\mathbf{Z}}$. The output of the SFA is given by:

$$\mathbf{c}_j = \mathbf{R}^T (\mathbf{S}^T \bar{\mathbf{z}}_j - \mathbf{S}^T \boldsymbol{\mu}_{\mathbf{z}}) = \mathbf{W}^T (\bar{\mathbf{z}}_j - \boldsymbol{\mu}_{\mathbf{z}}) \quad (4.13)$$

The ordering, in terms of slowness, of the functions \mathbf{c}_j , is provided by the order of the components in \mathbf{R} which is governed by the eigenvalues in \mathbf{H} ². The slowest function is related to the smallest eigenvalue and the next larger eigenvalue gives the second slowest function, etc.

Unfortunately, this batch processing approach of SFA is not suitable for online applications because of its expensive storage limitation (Kompella et al., 2012). Therefore, an incremental version of SFA is proposed to overcome this issue. Incremental Kernel SFA algorithm does not rely on any predefined training images for processing. It discovers the temporal variations in a video stream online without pre-image computation.

4.1.1 Incremental Kernel Slow Feature Analysis

Incremental Kernel Slow Feature Analysis updates slow features, incrementally so that it can process new input data by incrementally updating the data mean and whitening projections. In this thesis I have use the idea of SFA developed by Liwicki et al. (2013). However, instead of using complex gradient based kernel computed in Krein space (Liwicki et al., 2012), I have utilized the method of reproducing kernel in Hilbert space.

Suppose a data matrix $\mathbf{X}_A = [\mathbf{x}_1 \cdots \mathbf{x}_n] \in \mathbb{R}^{m \times n}$. In principle I non-linearly map \mathbf{X}_A to a higher dimensional space \mathcal{F} using the function $\Phi : \mathbb{R}^m \longrightarrow \mathcal{F}$. Using Φ , I transform \mathbf{X}_A into $\Phi_A = [\phi(\mathbf{x}_1) \cdots \phi(\mathbf{x}_n)]$. The map Φ is induced by a kernel function $\kappa(\cdot, \cdot)$ that allows us to evaluate inner products in new space \mathcal{F} .

$$\kappa(\mathbf{a}, \mathbf{b}) = \phi(\mathbf{a}) \cdot \phi(\mathbf{b}), \text{ with } \mathbf{a}, \mathbf{b} \in \mathbb{R}^m \quad (4.14)$$

The mapping function ϕ belongs to a space that has the structure of a reproduced kernel Hilbert space (RKHS) (Shawe-Taylor & Cristianini, 2004). Consider the matrix

²Suppose first K corresponding eigenvalues are represented by $\lambda_1, \dots, \lambda_K$. The order of these eigenvalues determines the order of slowest function, for example the smallest value of eigenvalue is related to the slowest function and the next larger eigenvalue represent second slowest function ($\lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_K$).

$\mathbf{K} = \Phi_A^T \Phi_A$. By using $\kappa(\cdot, \cdot)$, $\Phi_A^T \Phi_A$ can be evaluated without having to perform the mapping Φ since $\Phi_A^T \Phi_A$ contains only dot products between the $\phi(\mathbf{x}_i)$ s. Based on new transformations, the optimization problem of SFA can be reformulated as:

$$\min_R \text{tr}(\mathbf{R}^T \mathbf{S}^T \dot{\mathbf{K}} \dot{\mathbf{K}}^T \mathbf{S} \mathbf{R}), \text{ s.t. } \mathbf{R}^T \mathbf{S}^T \bar{\Phi}_A \bar{\Phi}_A^T \mathbf{S} \mathbf{R} = \mathbf{I} \quad (4.15)$$

where $\dot{\mathbf{K}}$ is the derivative of the centered kernel matrix $\bar{\mathbf{K}}$ such that $\dot{\mathbf{K}} = \bar{\mathbf{K}} \mathbf{P}_n \mathbf{M}_{n-1}$. The centring matrix is denoted by $\mathbf{M}_n = \mathbf{I}_n - \frac{1}{n} \mathbf{1}_{n \times n}$ and \mathbf{P}_n is an $n \times (n-1)$ matrix with the elements $\mathbf{P}_n(i, i) = -1$ and $\mathbf{P}_n(i+1, i) = 1$.

Let us assume a new data matrix $\mathbf{X}_B \in \mathbb{R}^{m \times i}$ where $\Phi_B = \phi(\mathbf{X}_B)$. I want to incrementally find the whitening projections and update the slow features to incorporate new data patterns such that the whole information is represented by the concatenation of Φ_A and Φ_B as $\mathbf{X}_C = [\Phi_A \ \Phi_B]$.

Let μ_A and μ_B be the mean of Φ_A and Φ_B respectively such that:

$$\mu_A = \Phi_A \left(\frac{1}{n_A} \mathbf{1}_{n_A \times 1} \right) \text{ and } \mu_B = \Phi_B \left(\frac{1}{n_B} \mathbf{1}_{n_B \times 1} \right) \quad (4.16)$$

where Φ_A contains n_A data samples Φ_B consists of n_B input vectors.

The mean μ_C of overall data \mathbf{X}_C is updated as (Chin & Suter, 2007):

$$\mu_C = \frac{n_A}{n_A + n_B} \mu_A + \frac{n_B}{n_A + n_B} \mu_B \quad (4.17)$$

Let $\bar{\Phi}_A$ and $\bar{\Phi}_B$ be the centered data matrix of Φ_A and Φ_B respectively, computed through subtracting the data from its mean as:

$$\bar{\Phi}_A = \Phi_A (\mathbf{I}_{n_A} - \beta_A) \text{ and } \bar{\Phi}_B = \Phi_B (\mathbf{I}_{n_B} - \beta_B) \quad (4.18)$$

where $\beta_A = ((1/n_A) \mathbf{1}_{n_A \times 1} \mathbf{1}_{1 \times n_A})$ and $\beta_B = ((1/n_B) \mathbf{1}_{n_B \times 1} \mathbf{1}_{1 \times n_B})$. Similarly, I update the

centered matrix of overall data matrix \mathbf{X}_C as: $\bar{\mathbf{X}}_C = \mathbf{X}_C - \boldsymbol{\mu}_C$

Unit Variance and Incremental Whitening: Consider the matrix $\bar{\mathbf{K}}$ such that:

$$\bar{\mathbf{K}} = \bar{\boldsymbol{\Phi}}_A^T \bar{\boldsymbol{\Phi}}_A = (\mathbf{I}_{n_A} - \boldsymbol{\beta})^T \boldsymbol{\Phi}^T \boldsymbol{\Phi} (\mathbf{I}_{n_A} - \boldsymbol{\beta}) \quad (4.19)$$

The eigenvalue decomposition of $\bar{\mathbf{K}}$ is computed as $\mathbf{P}\boldsymbol{\Lambda}\mathbf{P}^T$. Via kernel SVD (Shawe-Taylor & Cristianini, 2004), I compute the singular value factorization of $\bar{\boldsymbol{\Phi}}$ as:

$$\left[\bar{\boldsymbol{\Phi}} \mathbf{P} \boldsymbol{\Lambda}^{-\frac{1}{2}} \right] \left[\boldsymbol{\Lambda}^{\frac{1}{2}} \right] \left[\mathbf{P}^T \right] = \mathbf{U} \mathbf{D} \mathbf{V}^T \quad (4.20)$$

I compute the matrix \mathbf{S} which whitens the overall data matrix. For this I incrementally compute the SVD of the concatenated matrix such that $\bar{\mathbf{X}}_C : [\bar{\boldsymbol{\Phi}}_A \ \bar{\boldsymbol{\Phi}}_B] = \mathbf{U}' \mathbf{D}' \mathbf{V}'^T$. Let $\tilde{\boldsymbol{\Phi}}_B$ be the component of $\boldsymbol{\Phi}_B$ orthogonal to \mathbf{U} and $\mathbf{U}' = [\mathbf{U} \ \tilde{\boldsymbol{\Phi}}_B]$ (computed through QR decomposition (Levey & Lindenbaum, 2000)). The concatenated matrix can be represented in partitioned form (Brand, 2002) as:

$$\begin{aligned} \bar{\mathbf{X}}_C : [\bar{\boldsymbol{\Phi}}_A \ \bar{\boldsymbol{\Phi}}_B] = \\ [\mathbf{U} \ \tilde{\boldsymbol{\Phi}}_B] \begin{bmatrix} \mathbf{D} & \mathbf{U}^T \bar{\boldsymbol{\Phi}}_B \\ 0 & \tilde{\boldsymbol{\Phi}}_B (\bar{\boldsymbol{\Phi}}_B - \mathbf{U} \mathbf{U}^T \bar{\boldsymbol{\Phi}}_B) \end{bmatrix} \begin{bmatrix} \mathbf{V} & 0 \\ 0 & \mathbf{I} \end{bmatrix}^T \end{aligned} \quad (4.21)$$

Let

$$\boldsymbol{\Psi} = \begin{bmatrix} \mathbf{D} & \mathbf{U}^T \bar{\boldsymbol{\Phi}}_B \\ 0 & \tilde{\boldsymbol{\Phi}}_B (\bar{\boldsymbol{\Phi}}_B - \mathbf{U} \mathbf{U}^T \bar{\boldsymbol{\Phi}}_B) \end{bmatrix} \quad (4.22)$$

which is a square matrix of size $k + i$ where k is the number of singular values in \mathbf{D} .

Computing the SVD of $\boldsymbol{\Psi} = \hat{\mathbf{U}} \hat{\mathbf{D}} \hat{\mathbf{V}}^T$ to diagonalize the matrix and substituting into (4.21)

yields the SVD of $\bar{\mathbf{X}}_C : [\bar{\Phi}_A \bar{\Phi}_B]$:

$$\bar{\mathbf{X}}_C = ([\mathbf{U} \tilde{\Phi}_B] \hat{\mathbf{U}}) \hat{\mathbf{D}} \left(\hat{\mathbf{V}}^T \begin{bmatrix} \mathbf{V}^T & 0 \\ 0 & \mathbf{I} \end{bmatrix} \right) = \mathbf{U}' \mathbf{D}' \mathbf{V}'^T \quad (4.23)$$

Since, I am only interested in computing \mathbf{U}' and \mathbf{D}' , \mathbf{V}' , whose size scales with the number of observed data, need not to be computed. Thus, I only need to calculate the SVD of matrix Ψ for the incremental update which is defined as:

$$\mathbf{U}' = [\mathbf{U} \tilde{\Phi}_B] \hat{\mathbf{U}} \quad \text{and} \quad \mathbf{D}' = \hat{\mathbf{D}} \quad (4.24)$$

Therefore, the projection which whitens the signal is computed as $\mathbf{W} = \mathbf{U}' \mathbf{D}'^{-1}$.

Slow Feature Update: Based on the forward difference approximation the derivative of the data is calculated. Thus, suppose $\dot{\Phi}_A$, $\dot{\Phi}_B$ and $\dot{\mathbf{X}}_C$ represents the time derivatives of Φ_A , Φ_B and \mathbf{X}_C , respectively. Let us assume there are n_A samples represented in $\dot{\Phi}_A$. Similarly, I assume that new dataset $\dot{\Phi}_A$ consists of n_B samples. We first find the centred data matrix of the newly observed elements represented by $\dot{\Phi}_B$. Thus, from Ross et al. (2008) we can update the overall data matrix as:

$$\dot{\mathbf{X}}_C \dot{\mathbf{X}}_C^T = \dot{\Phi}_A \dot{\Phi}_A^T + \dot{\Phi}_B \dot{\Phi}_B^T + \frac{n_A n_B}{n_A + n_B} (\dot{\mu}_A - \dot{\mu}_B)(\dot{\mu}_A - \dot{\mu}_B)^T \quad (4.25)$$

where $\dot{\mu}_A$ and $\dot{\mu}_B$ represents the mean of time derivative patterns $\dot{\Phi}_A$ and $\dot{\Phi}_B$, respectively. The updated mean of overall data matrix is calculated analogous to Eq. (4.17). Finally I calculate the new feature function by computing the Eigen decomposition of $\mathbf{S}^T \dot{\mathbf{X}}_C \dot{\mathbf{X}}_C^T \mathbf{S}$ as $\mathbf{R} \mathbf{H} \mathbf{R}^T$ which gives our final output. Via the kernel method, the above process is rendered practicable without explicitly evaluating the mapping Φ .

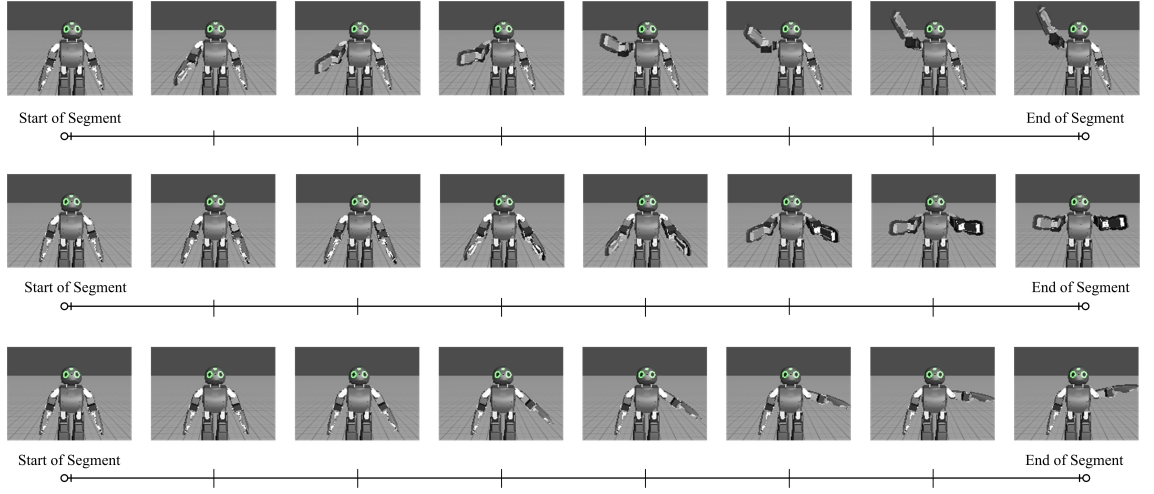


Figure 4.2: Segmentation result of behavioural sequence of motion captured. “*Start of Segment*” and “*End of Segment*” refers to the boundaries of the beginning and end of the action.

4.1.2 Episodic Segmentation

For episodic segmentation of actions from online stream of visual data, the consecutive frames with large differences in their slow feature values are used. Eq. (4.1) can be interpreted as the sum of squared Euclidean distance of the slow features computed between consecutive images. Suppose we have data \mathbf{z}_i , I define the δ as change detected in data after time t , as the squared Euclidean difference in slow features among its previous data.

$$\delta_l(\mathbf{z}_i) = (\mathbf{z}_i - \mathbf{z}_{i-1})^T \mathbf{W}_{l_t} \mathbf{W}_{l_t}^T (\mathbf{z}_i - \mathbf{z}_{i-1}) \quad (4.26)$$

where l is the number of utilized slow features.

In order to compare the change between the current frame and the previous time frames, I utilize the change of all the previous time steps. Therefore, I need to compute the average change without keeping the previous signals in the memory. The significant ratio ζ of the current and mean change is calculated to judge how substantial the change

at current step is:

$$\zeta = \frac{(t-1)\delta_{l_{t-1}}(\mathbf{z}_t)}{\mu_{l_{t-1}}} > \tau \quad (4.27)$$

where τ is the threshold value determined manually. Since the calculation of eigenvalues is done as a part of incremental Kernel SFA, therefore, I do not require previous samples because the sum of k largest eigenvalues in \mathbf{H} is nearly equivalent to $\mu_{l_{t-1}} = \sum_1^{t-1} \delta_{l_{t-1}}(\mathbf{z}_i)$. The significance ratio of the current and average change is calculated to judge how substantial the change at current step is.

4.2 Summary

In this chapter I have developed the on-line segmentation method utilizing visual data only instead of relying on the kinematic data. The proposed Incremental Kernel SFA algorithm searches for the suitable slow features in the images. After finding these features the significant ratio among the captured frames was calculated. Incremental Kernel SFA needs not to calculate this significant ratio on all the previous data, which makes it suitable for online applications.

CHAPTER 5 – INCREMENTAL ONLINE LEARNING

For incremental learning I have proposed novel Topological Gaussian Adaptive Resonance Hidden Markov Model (TGAR-HMM) (Dawood et al., 2013). In the proposed probabilistic architecture, the structure of the model, number of states and required probabilities are updated incrementally based on the observation sequence. The proposed model also acquires new information without corrupting previously learned data in a stable and a self-organizing fashion. The algorithm is based on incrementally learning spatio-temporal behavioural sequences by developing the graph based structure of the behaviour patterns in the form of a topological map. This mechanism is accomplished by developing a novel probabilistic neural architecture based topological mapping algorithm; called Topological Gaussian Adaptive Resonance Map (TGARM). The topological map compactly describes the environment as a collection of nodes linked by edges.

Adaptive Resonance Theory developed by Grossberg and Carpenter (Carpenter & Grossberg, 2010), models the cognitive and neural theory of how brain independently learns to categorize and recognize the events in the dynamic environment. The prominent features of this family of neural networks led the engineers to design various models such as ART-1 (Carpenter & Grossberg, 1987b) (for binary input patterns), ART-2 (Carpenter & Grossberg, 1987a) (for analog and binary input patterns) and Fuzzy ART (Carpenter et al., 1991) (combination of fuzzy logic and ART). However, learning complex spatio-temporal sequences through ART networks is still under development. Seyhan et al. (2013) developed a behaviour learning model for simple and complex actions in robot using HMM and a correlation based ART (CobART) network. CobART is a type of ART 2 network. The motion primitives acquired from the CobART are modelled through HMM to represent a relation between these motion primitives. The model generates different

categories for the same behaviours but with slight variation between them, thus providing a correlation between the motion patterns. The model learns the spatio-temporal sequences, however, the structure of the Behaviour HMM proposed by them is fixed and cannot grow incrementally.

In proposed architecture, an HMM can be considered as graph whose nodes represent states attainable by the object and whose edges represent transitions between these states. The system is assumed to be at a particular state and develop stochastically at discrete time steps by following the graph edges according to a transition probability. TGAR-HMM is described as a time evolving HMM with continuous observation variables, where the number of HMM states, structure and probability parameters are updated every time. Structurally, TGAR-HMM are similar to the standard HMMs, however, the transition structure and the number of states are not constant but vary as more input observation sequences are processed.

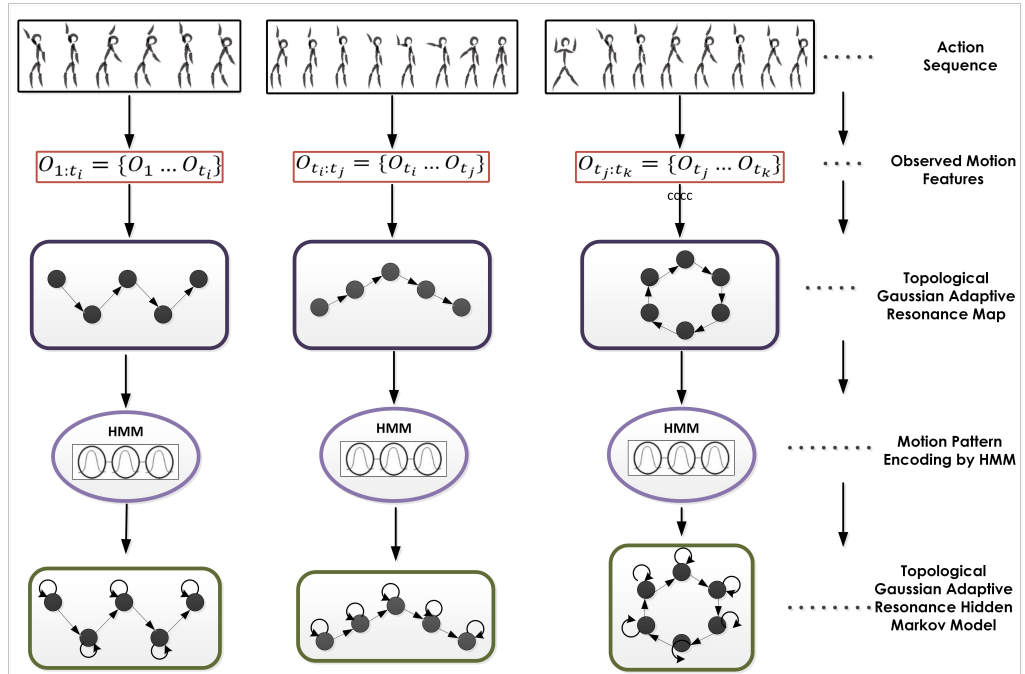


Figure 5.1: Overview of TGAR-HMM architecture. The observed behavior sequence is first arranged through topological map. This topological map is then used to update the state structure for estimating the optimal number of states and transition probabilities among these states.

The main intuition behind this model is that, firstly, the structure of the model should

consider the spatial structure of the state-space discretization, where the transition among discrete states are only permitted if the corresponding regions are neighbors. Hence, structure learning essentially consists of estimating the suitable space discretization from the observed data and identifying the neighboring regions. Secondly, in real world, data patterns are dynamic such that a specific behavioural pattern cannot be presumed to be independent of its predecessors. Processing such dynamic patterns vary fundamentally from treating static entities because the temporal sequence and correlation of the behavioural patterns being observed must be taken into account. I have addressed these issues by designing TGARM.

Figure 5.1 shows the graphical representation of the learning architecture. The observed motion elements (joint angle values) are first organized through the topological map consisting of nodes and edges. This map is then used to update the state structure for estimating the optimal number of states. After the organization of the data, the temporal sequence is learned through the TGAR-HMM, where each node represents a state of the HMM while an edge between two nodes represents the transition between these states. This state space distribution allows transition among neighbouring states only. In order to select the appropriate structure of the HMM or select the optimum numbers of HMM states, topologically arranged data sequence is employed. The structure of the model and its parameters representing the probabilities are updated with the acquisition of new observed data.

5.1 Incremental Learning

Hidden Markov Model is a doubly stochastic model with an underlying Markov process which is not directly observable (hidden) but can only be visible through sequence of observed symbols in each state (Rabiner, 1989). HMM explicitly includes time, resulting in efficient learning of temporal sequences. Each state is connected by transitions

between the states and generates an output pattern. Figure 5.2 shows an example of left-to-right HMM where each motion feature is encoded in the HMM state $\{s_1, s_2, \dots, s_n\}$ and allows the observation symbol, $b_i(\cdot)$, to be emitted from each state. The probability of moving from one state to another is given by transition probabilities, a_{ij} .

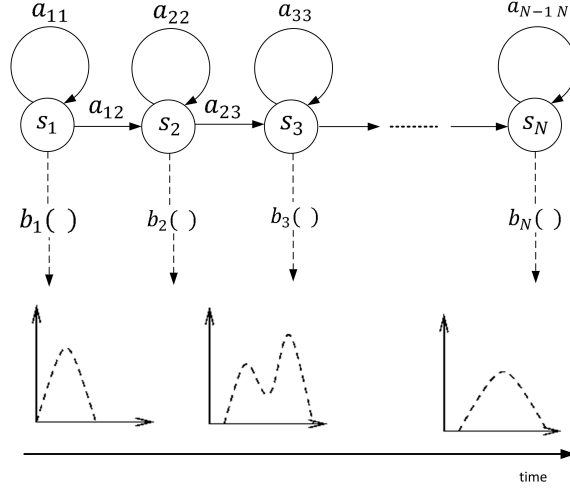


Figure 5.2: An illustration of motion sequences encoded in Hidden Markov Model (HMM).

An HMM is characterized by the following parameters:

- *State prior probabilities* ($\pi_i = P[s_0 = i]$) represents the prior probability for the corresponding state.
- *State transition probability matrix* ($A_{ij} = P[s_{t+1} = j | s_t = i]$) represents the probability of transition from state i to state j .
- *Observation probability distribution* ($B = P[O_t | s_t = i]$) represents the probability distribution of observation vector from state i . This distribution is represented by a Gaussian function denoted by the parameters $N(O_t | m_i, \sigma_i)$, where m_i and σ_i is mean vector and the covariance matrix for the i -th state in HMM.

These HMM parameters are denoted as $\lambda = \{\pi, A, B\} = \{\pi, A, m, \sigma\}$. Each hidden state in the HMM encodes an observed motion pattern where a sequence of motion patterns is estimated using the transition between these hidden states.

5.2 Motion Primitive Modelling – Topological Gaussian Adaptive Resonance Map

The segmented motion primitives are represented as the nodes linked with each other through edges. The function of the topological map is to develop a discrete structure of the continuous environment. Thus, the continuous data is now described as a sequence of discrete states (Figure 5.3). The edges connecting these nodes provide a transition among neighbouring nodes representing the continuous flow of data.

The input to the learning algorithm is composed of a series of discrete observations i.e. joint angle values from sensor reading describing the motion features. In addition, the observations are arranged in sequences $O_{1:T} = \{O_1, \dots, O_T\}$ ³ such that every sequence depicts the trajectory of action. The motion sequences are represented as the nodes linked with each other through edges. The function of the topological map is to develop a discrete structure of the continuous environment.

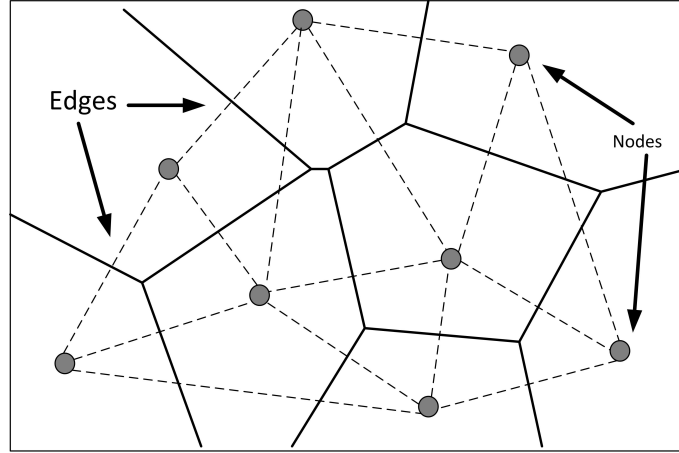


Figure 5.3: Example of space distribution through topological mapping showing nodes connected through edges.

When an input vector is given to TGARM, it finds the nearest node (winner) and the second nearest node (second winner) of the input vector. It subsequently judges if the input vector belongs to the same cluster of the winner or second winner using the vigilance criterion. The vigilance parameter is defined as the distance from the boundary to the center of Voronoi region Υ_i of node i . The input vector will be inserted to the

³For simplicity in notation I will represent the sequence $O_{1:T}$ as O_T .

network as a new node if the distance between the input vector and the winner or second winner is greater than the vigilance parameter. If the input vector is judged as belonging to the winner or the second winner, and if there is no connection between the winner and the second winner, connect the winner and second winner with a lateral connection or edge.

I assume the competitive Hebbian principle proposed by Martinetz et al. (1993) in topology preserving networks (TRN) to establish connections between neural nodes. The competitive Hebbian rule can be described as; “*for each input signal, connect the two closest nodes (measured by Euclidean distance) with an edge*”. It has been proved that each edge of the generated graph belongs to the Delaunay triangulation corresponding to the given set of reference vectors (Fritzke, 1995), and the resulting graph optimally preserves the topology in a very general sense (Martinetz et al., 1993).

TGARM model is based on the Gaussian mixture model of the input space where each Gaussian component represents a category node. The TGARM inherits the properties of neural networks capable of fast and constructive learning. TGARM has following properties:

- The structure grows incrementally by incorporating new knowledge without destroying previously learned data and adaptively responds to the information acquired from the environment.
- The parameters of each node in the topological map are updated for each input sample observed rather than after acquiring an entire data set beforehand.

Figure 5.4 shows the structure of the topological map model. The inputs are received from the robot sensors (joint angle values). Each input neuron is connected to the output neurons through the bottom-up weights; Moreover, each neuron in the output layer is connected to the input layer through the top-down weights. The bottom-up weights

(determined using (5.1) and (5.2)) provides an estimates of the likelihood that an input is a probable candidate for being a node or a category , whereas the matching function provides a confidence measure through the top-down weights. This confidence measure is defined by the vigilance parameter, ρ . The output layer creates a topological structure of the input data.

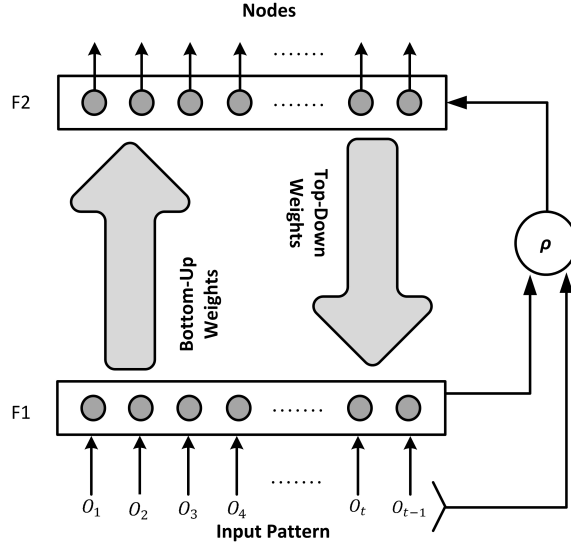


Figure 5.4: Architecture for creation of topological map.

Each node weights are defined by a vector ξ_j , a matrix Γ_j and n_j representing its mean, covariance and the learning rate, respectively. The learning rate or node count n_j represents the number of nodes or the number of input patterns learned by TGARM. The network is initialized with two parameters: the baseline vigilance parameter $\bar{\rho}$ which takes the values within the interval at $(0,1)$ and the initial covariance matrix. The variables that define the contents of the nodes are summarized in Table 5.1. This algorithm allows the observer to incrementally learn and update the structure of the model based on the observed motion patterns.

During learning, as the time progresses the nodes are added into the network and their associated weight values are updated. The learning algorithm grows its neural structure starting with the first node. The motion features, represented by joint angle values, are encoded as a Gaussian node in the structure and two nodes are connected with the

Table 5.1: Topological Gaussian Adaptive Resonance Map (TGARM) parameters

Parameters	Meaning
ω_J	Winning node.
ξ_j	Mean value – weight parameter.
Γ_j	Covariance Matrix – weight parameter.
ρ	Vigilance parameter initialized by the base vigilance parameter $\bar{\rho}$ with values (0, 1).
n_j	Node count or learning rate.

edges (Figure 5.3). This allows the flow of information among neighbouring nodes (De-launay Triangulation).

Algorithm 1 Algorithm for Topological Gaussian Adaptive Resonance Map

Require: :

Observation Vector O_t

Covariance Matrix Γ

Baseline Vigilance Parameter $\bar{\rho}$

Ensure: :

Nodes \mathcal{N}

Edges \mathcal{E}

- 1: Input the observation vector O_t .
 - 2: **if** There is no node in the network **then**
 - 3: Add O_t in the network as new node.
 $\mathcal{N} \leftarrow \mathcal{N} \cup \{O_t\}$; $n_i = 0$
 - 4: Update the weights of the node $\mathcal{N}(n, \xi, \Gamma)$ using Eq. (5.4)–(5.6)
 - 5: **else**
 - 6: Determine the winner node ω_J using (5.1) and (5.2)
 - 7: Determine the vigilance criterion for the winner node ω_J using Eq. (5.3)
 - 8: **if** calcVig < $\bar{\rho}$ **then**
 - 9: Add as a new node $\mathcal{N} \leftarrow \mathcal{N} \cup \{O_t\}$
 - 10: Update the weights of the ω_J (winner node) $\mathcal{N}(n_J, \xi_J, \Gamma_J)$ using Eq. (5.4)–(5.6)
 - 11: Add edge between the previous winner and current winner nodes $\mathcal{E} \leftarrow \mathcal{E} \cup \{(prevWinner, \omega_J)\}$
 - 12: **else**
 - 13: **if** calcVig $\geq \bar{\rho}$ **then**
 - 14: Reset the winner node and find a new winner from observation vector.
 - 15: Update the weights of previous winner node.
 - 16: Obtain the new observation vector O_t .
 - 17: If the learning is not completed, go to Step 6 to process the next observation.
 - 18: **end if**
 - 19: **end if**
 - 20: **end if**
-

This algorithm allows the observer to incrementally learn and update the structure of the model based on the observed motion patterns. The algorithm for topological mapping

consists of following steps:

- **Matching (Winner Node Selection):** During learning, a winning node ω_J is selected from an input pattern based on the highest probability. Since each node is represented by Gaussian components defined by the mean values, and the covariance matrix Γ_j , therefore, the conditional density of O_t given the winning node j or the bottom-up input activation value of a node is calculated as:

$$p(\mathbf{O}_t|j) = \frac{1}{(2\pi)^{M/2}|\Gamma_j|^{1/2}} \exp\left[-\frac{1}{2}(\mathbf{O}_t - \boldsymbol{\xi}_j)^T \Gamma_j^{-1}(\mathbf{O}_t - \boldsymbol{\xi}_j)\right] \quad (5.1)$$

where M is the dimensionality of the input motion patterns. For each input pattern the activation value is calculated using (5.1) and the neuron with highest activation value is selected using (5.2):

$$J = \arg \max_j P(\mathbf{O}_t|j) \quad (5.2)$$

- **Resonance:** The node represented by its weights ($\omega_J = (\boldsymbol{\xi}_J, \Gamma_J)$) determined by mean and covariance is only allowed to be updated if the resonance criterion or matching between the given input and the selected winner node is fulfilled. A node ω_J passes the vigilance criterion if its matching function value exceeds the vigilance parameter value ρ , that is if:

$$\exp\left[-\frac{1}{2}(\mathbf{O}_t - \boldsymbol{\xi}_j)^T \Gamma_j^{-1}(\mathbf{O}_t - \boldsymbol{\xi}_j)\right] \geq \rho \quad (5.3)$$

- **Node Addition:** The vigilance is a measure of similarity between the input and the node's mean relative to its standard deviation. If the winning node fails to pass the vigilance test (5.3), the current winner node is disqualified and its activation value

is reset. Then, the observed pattern is searched for the new winning best matching neuron. If no satisfactory neuron is found, a new neuron representing the input pattern with $n_J = 0$ is integrated satisfying the resonance.

- **Weight Updating:** When the winning neuron, satisfying the resonance condition representing the input pattern is selected, its parameters, i.e. count, mean, and variance are updated using (5.4) – (5.6).

$$n_J = n_J + 1 \quad (5.4)$$

$$\xi_J = (1 - \frac{1}{n_J})\xi_J + (\frac{1}{n_J})\mathbf{O}_t \quad (5.5)$$

$$\Gamma_J = (1 - \frac{1}{n_J})\Gamma_J + (\frac{1}{n_J})(\mathbf{O}_t - \xi_J)(\mathbf{O}_t - \xi_J)^T \quad (5.6)$$

- **Edge Addition:** When the resonating neuron is determined, a lateral connection or an edge is established between the current and the previous winner node to map the temporal correlation between the data. This mechanism will provide a stable architecture for providing a link between the previously learned knowledge and integrate newly observed data.

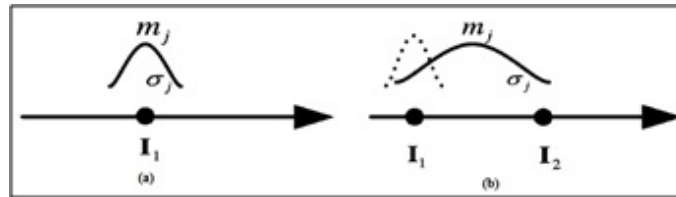


Figure 5.5: GART learning: (a) Gaussian distribution with mean equal to the input pattern I_1 that was first encoded; (b) At the presentation of new pattern, I_2 , the Gaussian parameters are modified to incorporate new information.

The performance of the TGARM depends on two parameters: the vigilance parameter ρ , and the initial covariance matrix γ . The vigilance parameter directly influences the formation of new nodes when novel information is detected. On one hand, for higher

values of the vigilance parameter, the system becomes more sensitive to the changes in the input and the network becomes complicated. On the other hand, for the lower values of the vigilance parameter the system becomes less sensitive and faster. Therefore, the decision about the vigilance parameter value greatly influences the convergence and recognition properties of the system. Furthermore, the generalization performance of the network is greatly affected by the selection of values for initial covariance matrix.

5.3 Updating Structure and Parameters of HMM

After updating the topological map, the structure of HMM is also updated based on the added nodes and edges. The structure of HMM is updated whenever a new behavior is observed. For every node added in the topological map, a state in the HMM is also added. Each added state is initialized with the prior probability $\pi_i = \pi_0$ and self-transition probability $a_{i,i} = a_0$, where i represents the new node. Similarly, for addition of every new node and the new edges (i, j) connecting these nodes, the transition probabilities are also initialized with the state transition probability value $a_{i,j} = a_0$.

Table 5.2: TGAR-HMM parameters

Parameters	Meaning
π_i	State prior probability – Every node added in the map is initialized with the state prior value.
a_{ij}	State transition probability – Updated through the edges connecting two nodes in TGARM.
m_i	The mean value for Gaussian in HMM – Updated through topological map for each node ($m_i = \xi_i$).
σ_j	The covariance matrix for each node in HMM – Updated through topological map for each node ($\sigma_i = \Sigma_i$).
O_t	Observation probability distribution – Represented through Gaussian distribution with parameters $N(O_t m_i, \sigma_i)$.

After learning the HMM structure, the parameters of HMM are also learned. The mean value and the covariance values related to each Gaussian observation are updated during the structure (topological map) learning process discussed in the previous section (5.2). However, the remaining parameters such as transition probability and state prior

probabilities must be re-estimated. These parameters are updated using the Expectation Maximization (EM) algorithm. Traditionally, Baum Welch algorithm (Rabiner, 1989) (which is a type of EM algorithm) is used for learning the initial state probability distribution and the state transition model. The transition probability and state prior probability are estimated using (5.7) and (5.8).

$$\bar{a}_{ij} = \frac{\sum_{t=1}^{T-1} \alpha_t(i) a_{ij} b_j(O_{t+1}) \beta_{t+1}(j)}{\sum_{t=1}^{T-1} \alpha_t(i) \beta_t(i)} \quad (5.7)$$

$$\bar{\pi}_i = \frac{\alpha_1(i) \beta_1(i)}{P(O|S_i)} \quad (5.8)$$

In equations Eq. (5.7) and Eq. (5.8) the α_i and β_i represent the forward and backward variables (Rabiner, 1989). The forward and backward variables computes the posterior margins of all hidden variable given a sequence of observations. Table 5.3 explains the recursive computation of these variables. $P(O|S_i)$ in Eq. (5.8) determines the joint observation probability.

Table 5.3: Recursive Computation of Forward and Backward variables.

Algorithm	Computing
Forward Variable	$\alpha_i(1) = \pi_i b_i(O_1).$ $\alpha_j(t+1) = \left[\sum_{i=1}^N \alpha_i(t) a_{ij} \right] b_j(O_{t+1})$
Backward Variable	$\beta_i(T) = 1$ $\beta_i(i) = \sum_{j=1}^N a_{ij} b_j(O_{t+1}) \beta_j(t+1)$

In order to update the parameters incrementally for new observed data, an incremental learning rule is applied as follows:

$$\bar{a}_{ij} = \frac{\bar{a}_{ij} + (N_p - 1)a_{ij}}{N_p} \quad (5.9)$$

$$\bar{\pi}_i = \frac{\bar{\pi}_i + (N_p - 1)\pi_i}{N_p} \quad (5.10)$$

where N_p is the number input patterns that has been observed until the current time.

The forward variable, $\alpha_t(i)$, represents the probability of partial observation sequence until time t ending up in state i , given the model. The mathematical form of forward variable is defined as:

$$\alpha_t(i) = P(O_1 O_2 \cdots O_t, q_t = S_i | \lambda) \quad (5.11)$$

The backward variable, $\beta_t(i)$, represents the probability of the partial observation sequence from time $t + 1$ to the end of observation sequence, given that the model was in state s_i at time t . The formal definition of $\beta_t(i)$ is given as:

$$\beta_t(i) = P(O_{t+1} O_{t+2} \cdots O_T, q_t = S_i | \lambda) \quad (5.12)$$

There are many alternate path to design HMM topologies, although there is no standard way to find out an optimal HMM configuration (Rabiner, 1989). A very customary conformation is the left-right configuration, where each state leads to itself, along with two forward connections. These forward links entail that the state can only transition to the state directly to its right (Figure 5.2).

5.4 Summary

In this chapter I have developed a novel architecture for incremental learning for continuous flow of motion patterns based on novel architecture called Topological Gaus-

sian Adaptive Resonance Hidden Markov Model (TGAR-HMM). The structure of the model is updated incrementally through a novel topological map. Based on this topological map, the model aggregates the information as observed and organize the acquired information in an efficient growing and self-organizing manner. The dynamic architecture grows incrementally to adapt to the new data from the environment. The fundamental characteristics of the network are the stable learning and fast convergence. As the new sequence of data is learned the network converges to create a stable topological structure of the input trajectory. Based on this feature, the proposed architecture does not suffer ruinous forgetting and accommodates the new information. The TGAR-HMM model efficiently learns and encodes the spatio-temporal patterns and computes the probability that observation sequences could be generated. Secondly, the novel HMM architecture adaptively selects the models structure based on the observed data and is not pre-defined based on some prior knowledge.

CHAPTER 6 – VISUOMOTOR ASSOCIATIVE MEMORY

When the agent (the robot) generates motor commands, the representations of these commands and the perceived effects of these command can be associated through Hebbian-like learning (Chaminade et al., 2008; Ogino et al., 2005). Thus, the proposed computational framework is based on the hypothesis stating: “motor babbling could induce acquisition of sensory-motor associations capable of sustaining early imitation skills”. The co-occurrent relationship between motor commands and sensory feedback during motor babbling might develop the associations between these two occurrences. Based on this associative relationship, when actions of some other agent are perceived, might lead to an automatic and spontaneous generation of the motor output. The proposal that associative learning could render the developmental link between automatic imitation and the perception of actions by mirror neurons is of particular interest. This attainment of sensory motor associations and its relation with mirror neurons and imitation have been discussed in literature (Heyes, 2001; Keysers & Perrett, 2004; Kuniyoshi et al., 2003).

Associative memory stores information in a distributed manner, which is recovered based on the association developed between stored contents (Hopfield, 1982; Kosko, 1988). Whenever a pattern, called a “key-vector”, is presented as an input, the associative memory is required to recall or return a stored memory pattern, called “response vector” associated with that particular key. The neural self-organization of information in context of associative memory is a major capability of the human mind (Tavan et al., 1990).

In literature the well-established methods are useful in representing the distribution of input patterns, for example, the conventional self-organizing map (SOM) (Kohonen, 1982) brings forth the topological mapping from a high-dimensional signal space to a

lower-dimensional structure. However, the pre-defined structure and size of the network inflicts restrictions on the growth of topological map. Similarly, the integration of “competitive Hebbian learning” and “neural gas” (Martinetz et al., 1993) also necessitates a predetermined knowledge pertained to the size of the network. Growing neural gas (Fritzke, 1995) confronts the weakness of a permanent increase in the number of nodes if the number of nodes is not pre-defined.

I have developed an associative memory, called Topological Gaussian Adaptive Resonance Associative Memory (TGAR-AM), structure using three-layered architecture, namely the input layer, the memory layer and the association layer. The input layer receives the sensory data, the memory layer encodes the received data in the form of a topological structure in an incremental manner, and the association layer formulates the associative relationship between the input patterns. The association between the memory patterns is developed based on the labels acquired through motion primitive segmentation. Therefore, the patterns that belong to different motion primitive segments are stored as different sub-network of the memory layer. Based on this theory, the patterns in the associative layer are learned incrementally without destroying previously stored information. The proposed associative memory system is able to memorize temporal sequence information as patterns with a consecutive relation. The proposed TGAR-AM has following properties:

- The associative memory (TGAR-AM) system store and recall non-binary patterns. Since, in the real world, information generally constituted real valued feature vectors, therefore, it is an essential requirement for associative memory systems to store and recall non-binary patterns (Shen et al., 2013).
- The system memorizes incrementally and associate new information without corrupting stored knowledge. Humans have the capability to memorize and learn novel

knowledge incrementally without destroying the information learned previously.

- The proposed associative memory system is able to memorize temporal sequence information as patterns with a consecutive relation.
- The TGAR-AM learns hetero-associative mappings between the patterns of generally different dimensions and distributions.

The structure of Topological Gaussian Adaptive Resonance Associative Memory (TGAR-AM) is based on TGARM. The Topological Gaussian Adaptive Resonance Map (TGARM) (Dawood et al., 2013) performs incremental topology representation without calling for a priori definition of the structure and size of the network. For each class of the input feature vectors, I employed TGARM to represent the distribution of that labelled class.

In addition to visuo-motor association, the associative memory is utilized for motion generation. The main task of behavior generation phase is to find the most likely motion primitive sequence to perform the observed behavioral action. For this purpose the desired behavioral action is presented as an image sequence to the associative module. Next, the label of the observed images is estimated using the auto-associative mode and the motion label associated with the observed image is selected. Then, observation is generated by estimating the most likely path sequence. The TGAR-HMMs observation-to-observation transition probabilities are used for this purpose to calculate the most likely path to generate the most likely motion primitive sequence. As a result, the sequence of motion primitives to achieve the given behavior is generated.

6.1 Self and Observed Action Association

TGAR-AM model consists of three layers the input layer, the memory layer and the association layer. The visual feature vectors and action features are provided as input

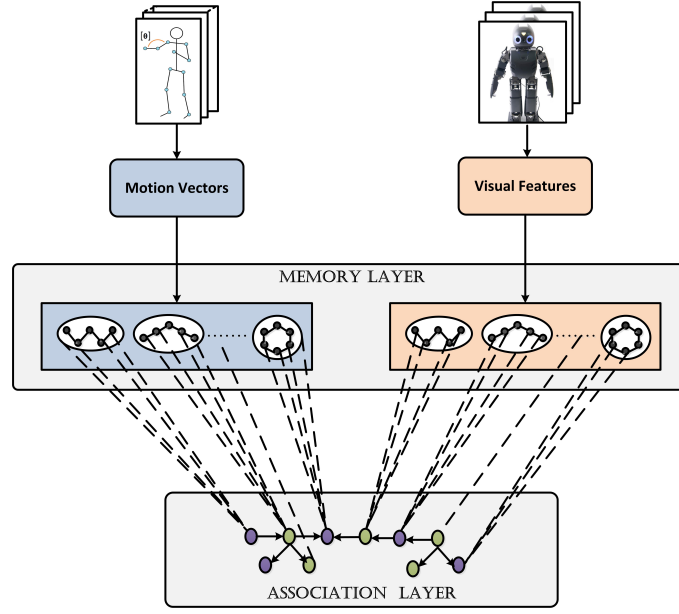


Figure 6.1: Structure of Associative Memory consisting of Memory Layer and Associative Layer.

to the memory layer. According to the labels of these input vectors, the memory layer stores these input patterns as a sub-network. If the label of the class of the input vector does not belong to an existing class in the memory layer, a new network representing the new class label is added to the layer. Otherwise, a node is added to the corresponding sub-network. The class labels of these sub-networks in the memory layer are transferred to the association layer. Using TGARM, the association is developed between the vision and action vectors. This association is represented through the edges between the vision and the action nodes. This association between the temporal sequences is represented through the edges between the vision and the action nodes.

6.1.1 Memory Layer

The proposed architecture for training of the memory layer is illustrated in Figure 6.2. The visual features are acquired from the Inc-KSFA while the action features are obtained from the robot sensors as joint angle values. When a feature vector is provided as input to the memory layer, if at that point there is no sub-network representing the class label of that input feature vector, then create a new sub-network with the input

vector as the first node. This new sub-network is represented with the class name of the input feature vector. If there is already a sub-network with the same class name as the input vector, then update the weight vector of the node of the sub-network representing that particular class label. Similar to TGARM, if there is no edge connecting the two nodes, then create an edge linking the two winning nodes (previous winner node and current winner node).

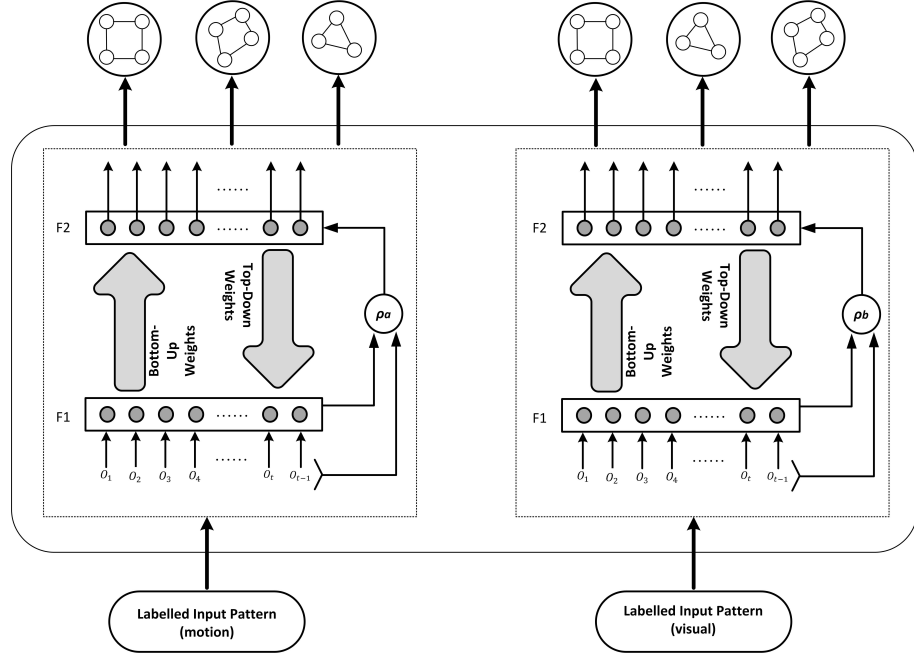


Figure 6.2: Learning mechanism of the memory layer. Visual features are represented by Inc-KSFA while action features are represented by joint angle values. For each class of the input feature vectors, TGARM is utilized to represent the distribution of that labelled class.

New classes are learned incrementally by adding new subnetworks; for example, learning new patterns belonging to one class is done incrementally by integrating new nodes to an existent subnetwork. The number of subnetworks in the memory layer is not fixed beforehand, rather determined incrementally based on the number of classes of input patterns.

6.1.2 Association Layer

The association layer builds an association between the vision vectors (key-vectors) and the action vectors (response-vectors) using their class labels, i.e., vision vectors (V_t)

belong to a visual feature class (v_t) and motion vectors (O_t) belong to an action features class (a_t). Each node in the association layer represents one class and all the nodes are connected through edges – the start of the edge indicates the key-class and the end of the edge points to the corresponding response-class (Figure 6.3). This develops an associative relationship joining the key-class and the response-class. During the learning of the association layer, an association paired data consisting of the key-vector and response-vector, is utilized as input vectors and incrementally transferred to the system. First, the TGARM algorithm (described in CHAPTER 5) is employed to memorize information of both the vision and the motion feature vectors. The class name of the new class is sent to the association layer. Similar to the memory layer, if the class label of the node in the memory layer does not exist in the association layer, a new node representing the new class label is added to the association layer. The weight of each node in the memory layer is selected from the corresponding weight of the sub-network in the memory layer.

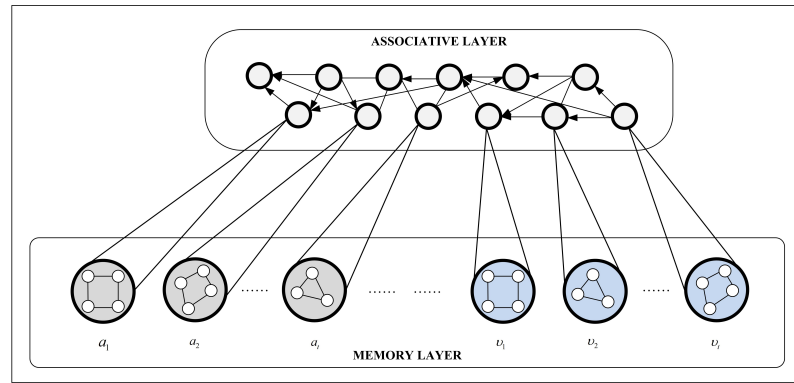


Figure 6.3: Learning mechanism of the Association Layer.

6.2 Associative Recall and Behaviour Generation

When a key-vector is presented as an input, the associative memory is required to recall the corresponding response vector associated with that particular key from the memory. The recall process employed both auto-associative (Kosko, 1988) and hetero-associative (Kosko, 1988) mechanism. Behavior generation phase (or recalling/generating

appropriate motor commands based on observed visual stimuli) can be described as a two-step problem:

- **Category Estimation:** Given the visual stimuli observation sequence represented by slow feature, the role of category estimation is to determine the label of the unlabeled input visual features. This is accomplished through the auto-associative recall process.
- **Motion Primitive Sequence Generation:** Given the category of the observed visual stimuli and HMM, the purpose of sequence generation step is to find the associated action category label. This is determined using the hetero-associative mode. After finding the associated category label, the corresponding most likely state sequence for motion generation is estimated through Viterbi algorithm (Rabiner, 1989).

In the first step of associative recall, the auto-associative mechanism is utilized. During auto-association mechanism, the system recognizes the key vector class resembling the input pattern stored in the memory. Later, once the class of the key-vector is determined using Algorithm 2, the hetero-associative mechanism is employed to recall paired-associative pattern. During this process, the key-vectors determined in the previous phase are presented to the system as cues, and the system recalls the appropriate paired items associated with that key vector.

For the associative recall process, I calculate the distance between the input vector (V_i) and the stored weight vector (N_i^T). If the distance ϑ between the two vector lies within the Voronoi region i.e., the distance is larger than the threshold (ρ or vigilance parameter), then the memorized pattern is recalled. Otherwise, the system fails to recall. The threshold value is determined using the vigilance parameter used during TGARM

Algorithm 2 Algorithm for Auto-associative Recall

```
1: Input the observation vector  $\mathcal{V}_t$ .
2: for all the nodes in the Memory Layer. do
3:   Calculate the weight sim of input vector as:
4:    $\vartheta_i(V_t) = N_i^T V_t - \frac{1}{2} \|N_i\|^2$  where  $N$  is the weight of the nodes in the memory layer.
5: end for
6: Find:  $\vartheta_k(V_t) = \max_{\forall nodes} \vartheta_i(\mathcal{V}_t)$ 
7: if  $\|V_t\|^2 - 2\vartheta_k(V_t) > \rho$ . then
8:   OUTPUT: Failed to Recall the memorized pattern.
9: else
10:  Find the node  $V_t$  corresponding to the sub-network  $v_t$ .
11: end if
```

learning.

$$\|V_t\|^2 - 2\vartheta_k(V_t) > \rho \quad (6.1)$$

where

$$\vartheta_k(V_t) = \max_{\forall nodes} \vartheta_i(V_t) \quad (6.2)$$

and

$$\vartheta_i(V_t) = N_i^T V_t - \frac{1}{2} \|N_i\|^2 \quad (6.3)$$

As discussed in Chapter 5, Section 5.2, the Topological Gaussian Adaptive Resonance Map separates input patterns into different Voronoi regions. In the association process, if an input feature vector dwells in one Voronoi region Υ , I assign the weight vector (represented by TGARM parameters) of the corresponding node i as the associative result. If the distance between the input vector and one node is greater than the similarity threshold (6.1), i.e., the radius of the Voronoi region, it means that the input key vector is beyond the attraction basin. If the input key vector is beyond the corresponding Voronoi regions for all nodes, then the key vector fails to recall the memorized pattern.

6.3 Summary

In this chapter I presented an associative memory architecture, called TGAR-AM, consisting of three layers, namely the input layer, the memory layer and the association layer. The memory layer encode the acquired data from the input layer in the form of a topological structure in an incremental manner. The association layer formulates the associative relationship between the input patterns. According to the labels of these input vectors, the memory layer stores these patterns as a sub-network. Using TGARM, association is developed between the vision (key-vector) and action vectors (response vector) based on the labels of these sub-networks. This association between the temporal sequences is represented through the edges between the vision and the action nodes.

CHAPTER 7 – EXPERIMENTAL RESULTS

In this chapter, I will discuss the experimental settings and analysis of the proposed architecture. The experiments were divided into two parts: in the first part the simulation experiments were conducted while in the second part the proposed architecture was evaluated for real-time robot application. The assessment of the proposed self-learning architecture was conducted through experimentation on open humanoid platform DARwIn-OP developed by Robotis Co. Ltd ³⁴. For simulation purposes, I used the Webots (Michel, 2004; Webots, 2004) simulator.

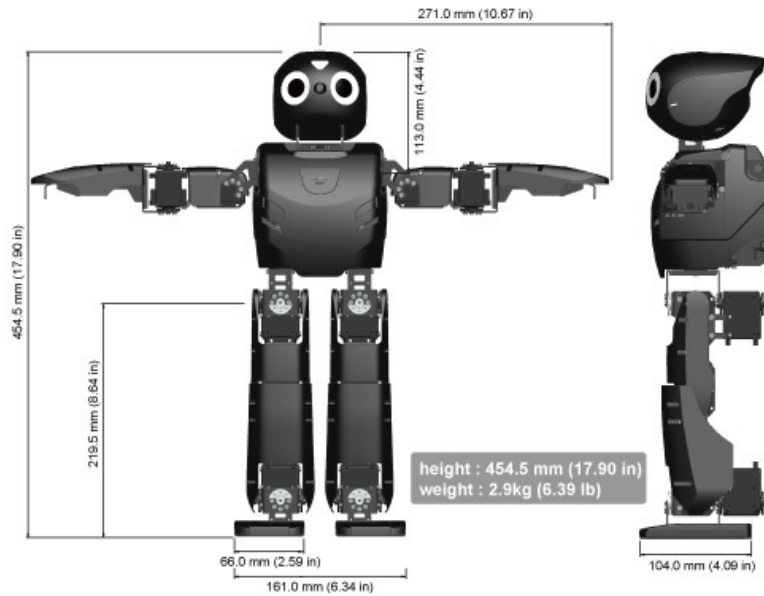


Figure 7.1: Kinematic structure of open humanoid platform DARwIn-OP. SOURCE:(Ha et al., 2011)

The 0.455m tall and 2.8kg DARwIn-OP has 20 degrees of freedom (Head: 2-DOF; Arm: 6-DOF; Leg: 12-DOF) with 3-axis accelerometer for posture estimation and balancing (Figure 7.1). The robot uses Robotis' Dynamixel MX-28 servo motors for the joints driven by an internal CM-730 Robotis servo-controller. The head contains a single USB-based camera connection with 2-Megapixel 640×480 resolutions (up to 1600×1200,

³Dynamic Anthropomorphic Robot with Intelligence (DARwIn-OP)

⁴http://www.robotis.com/xe/darwin_en

10fps or 1280×720, 30fps) for image processing. The camera is a high-definition camera that interfaces with the robot via the USB standard which provides detailed information.

7.1 Experimental Setup

The first set of experiments was conducted in a simulation environment to test the efficacy of the proposed framework. The validation of proposed mirror image based self-learning approach was performed on a test-bed consisting of two DARwIn-OP robots (Figure 7.2). Just as humans perceive their reflection in the mirror, in simulation environment, one robot acts as a demonstrator while the other robot observed these demonstrated actions as the mirror image reflection of the demonstrator. The algorithm was tested on video sequences of different actions captured by the robot's camera. At the same time the joint angle values of the robot are also recorded by the observer. The joint angles are obtained from the robot servo motors while it was performing random actions. These joint angle values are used for learning the observed action.

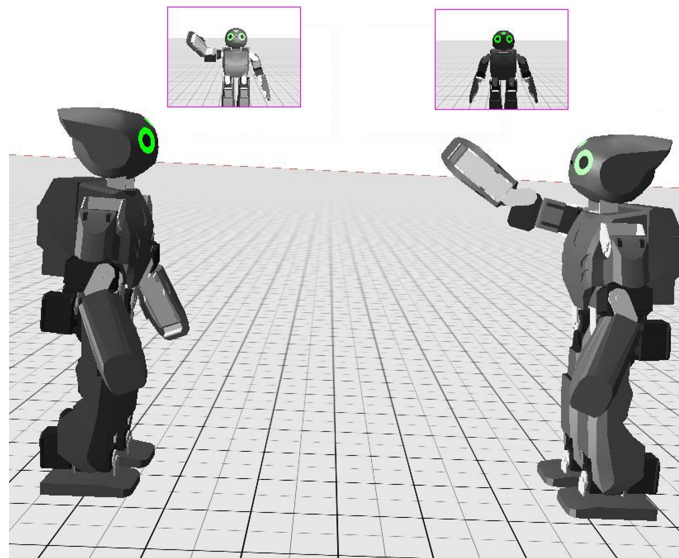


Figure 7.2: Simulation environment for experimentation consisting of two robots. One acts as a demonstrator (left robot), while the second acts as an observer (right robot).

To assess the application for computational framework in real-life situations, I used a real robot environment consisting of real DARwIn-OP humanoid robot. A camera is positioned on the monitor screen to create the mirror reflection environment. The camera

on the monitor projects the robot's action on the screen, while the robot's own monocular camera observes these projected self-images for processing. During motor babbling phase, the robot observes its own projected image on the screen during the random generation of actions, and processes the observed self-images for segmentation. In parallel the joint angles are also learned by the robot for each action performed.

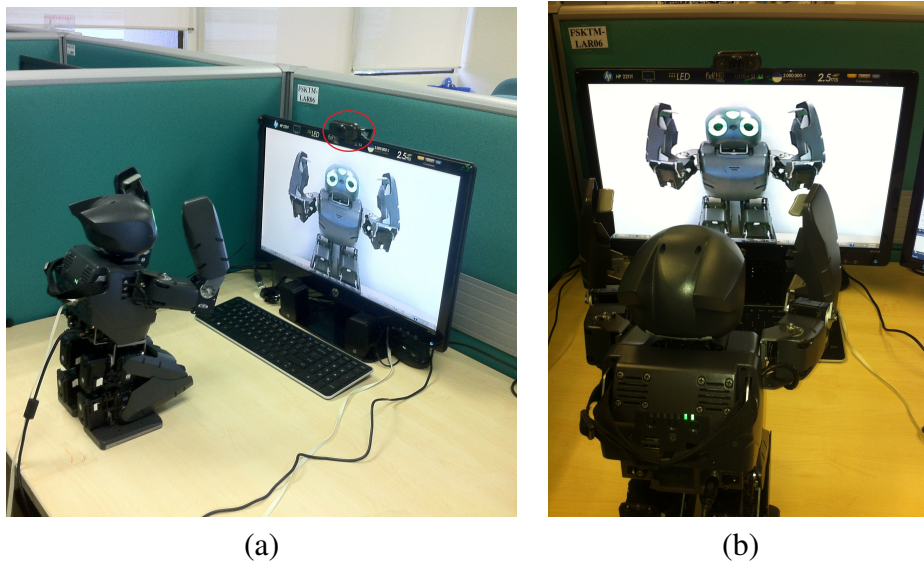


Figure 7.3: Robotic setup for the experimentation

During the learning process, the robot performs random arm movements and tries to estimate the joint angles of each joint involved in the action, along with analysing the frames grabbed from its head camera. In this case, the robot (self) and its own reflection (interpreted as another robot in simulation environment) moves at the same time during the learning phase. The robot babbled with its motor commands, gathered evidence of the motor commands and corresponding observations, and then learnt the relationship between this using Topological Gaussian Adaptive Resonance Associative Memory (TGAR-AM). During this process, the motor commands interpreted as motion elements (represented through joint angles in radians) are learned through Topological Gaussian Adaptive Resonance Hidden Markov Model (TGAR-HMM).

The dataset consists of a variety of different actions involving upper part of the body.

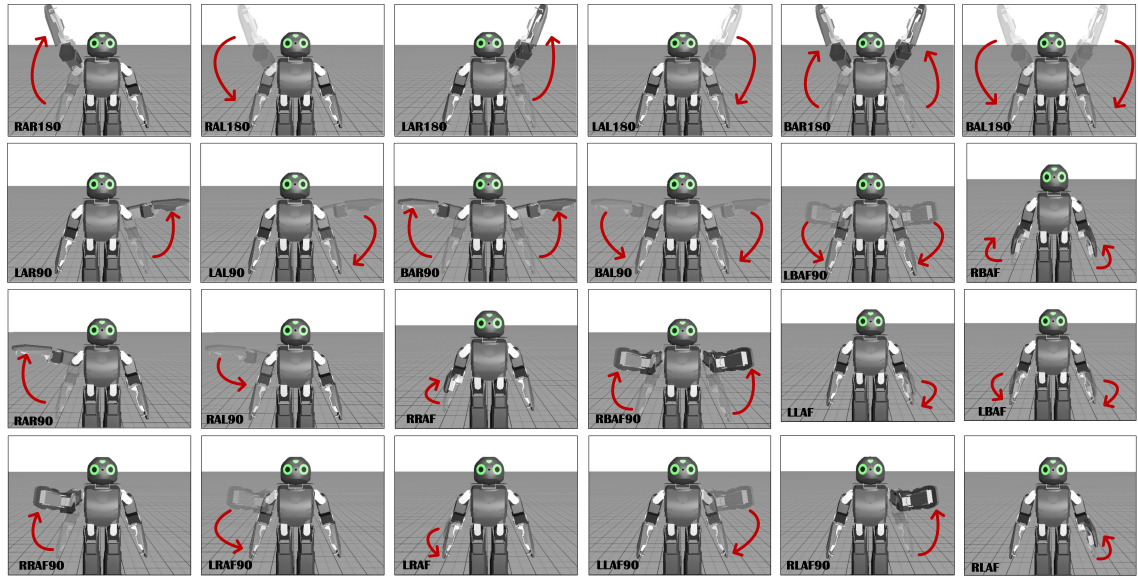


Figure 7.4: Illustration of different actions performed by the robot during experimentation.

Table 7.1: Summary of Different Types of Actions Performed and their identification accuracy

Motion Description	Label	Motion Description	Label
Right Arm Raise 180deg	RAR180	Lower Both Arms Front 90deg	LBAF90
Right Arm Lower 180deg	RAL180	Raise Both Arms Front 90deg	RBAF90
Left Arm Raise 180deg	LAR180	Lower Left Arm Front	LLAF
Left Arm Lower 180deg	LAL180	Raise Left Arm Front	RLAF
Both Arms Raise 180deg	BAR180	Lower Right Arm Front 90deg	LRAF90
Both Arms Lower 180deg	BAL180	Raise Right Arm Front 90deg	RRAF90
Left Arm Raise 90deg	LAR90	Lower Right Arm Front	LRAF
Left Arm Lower 90deg	LAL90	Raise Right Arm Front	RRAF
Right Arm Raise 90deg	RAR90	Lower Left Arm Front 90deg	LLAF90
Right Arm Lower 90deg	RAL90	Raise Left Arm Front 90deg	RLAF90
Both Arms Raise 90deg	BAR90	Lower Both Arms Front	LBAF
Both Arms Lower 90deg	BAL90	Raise Both Arm Front	RBAF

The variants of actions include standing up, raising and lowering left and right arm by 180deg one at a time, raising and lowering both arms by 180deg simultaneously, raising and lowering left and right arm by 90deg one at a time, raising and lowering left and right arm by 90deg one at a time. Table 7.1 summarizes the types of actions performed for testing. To access the efficiency of the proposed segmentation algorithm, the demonstrator performs these actions with different repeating intervals, i.e., the sequence of these actions are not fixed and are performed randomly. Some of these actions are performed with a pause between while others are executed fluidly to validate the efficiency of the proposed architecture. To generate visual representations for other perspectives (for e.g. 90° , 180° and 270°), not directly available from simulator, we used self-observed trajectories (0°) and rotated them correspondingly. Figure 7.4 shows the visualization of actions performed by the demonstrator. Each image in the figure shows different frames extracted from the action sequences.

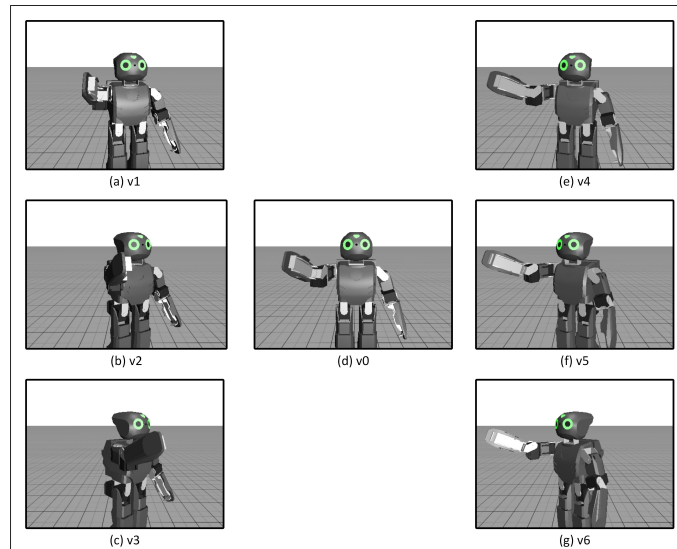


Figure 7.5: Examples of different types of perspectives. v0 represents the self-perspective, while the remaining images are captured from different viewing angles/perspectives of a particular action.

First, the experiments with the self-observing perspective are performed and the association is developed from that perspective symbolizing the PF pathway between STS and F5. The robot associates its own movements with their visual appearance on the

basis of TGAR-AM. Directly after this, assuming that the motor patterns are still residually active, the robot observes the same action from a different perspective. Later, the robot performs association with the behavioural actions observed from other different perspectives. Figure 7.5 shows the images of various view perspectives utilized during experimentation.

7.2 Motion Primitive Segmentation

The segmentation of the observed or demonstrated motion sequence enables the proposed framework to recognize and segment the visual effects of the actions. The raw image sequences acquired from robot camera are processed for motion primitive segmentation. In order to maintain simplicity, I presume that only one motion primitive is executed at a particular time. Compound motion primitives performed at the same time will be addressed later. Initially, the demonstrator is standing still and no feature points exhibit significant change. As soon as the robot starts moving the joints, change in feature values is recorded and the significant ratio is computed. Based on the significant ratio, the start and end of an action are computed.

Figure 7.6 shows the result of the Incremental Kernel SFA algorithm. Whenever a significant change in the captured frames is detected, the significant ratio value is increased when the action is completely performed, thus performing the segmentation on-line. Figure 7.6 shows the change in significant ratio along with the number of frames to segment the observed motion patterns into episodes of action. The segmentation algorithm commences with no a-priori knowledge of the motion patterns and the observed data is being segmented on-line by analysing the incoming data stream. I have also tested the segmentation algorithm on images obtained from different perspectives and summarized the results in Figure 7.7. These results show that the proposed Inc-KSFA algorithm performs the motion primitive segmentation irrespective of the view or perspective from

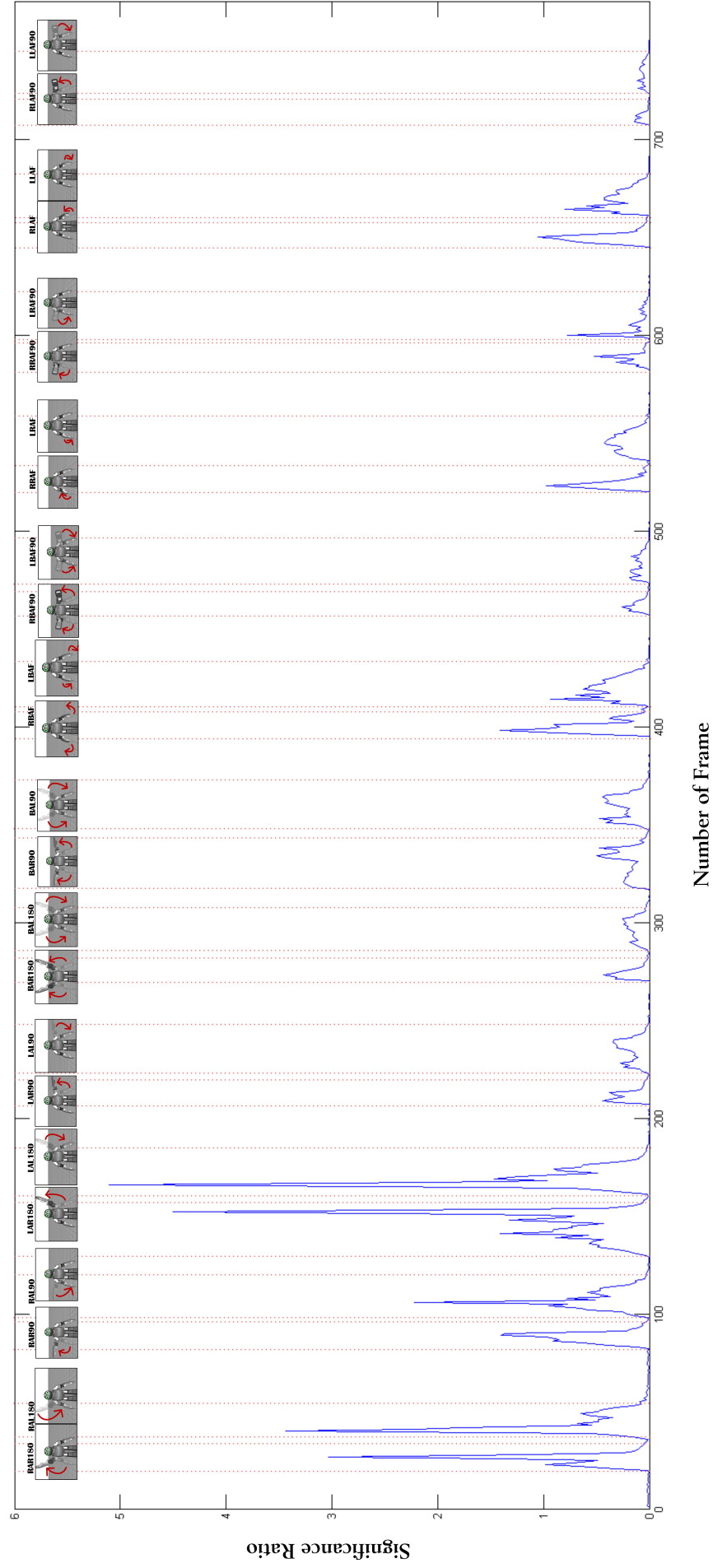


Figure 7.6: Output of the segmentation algorithm through Incremental Kernel Slow Feature Analysis.

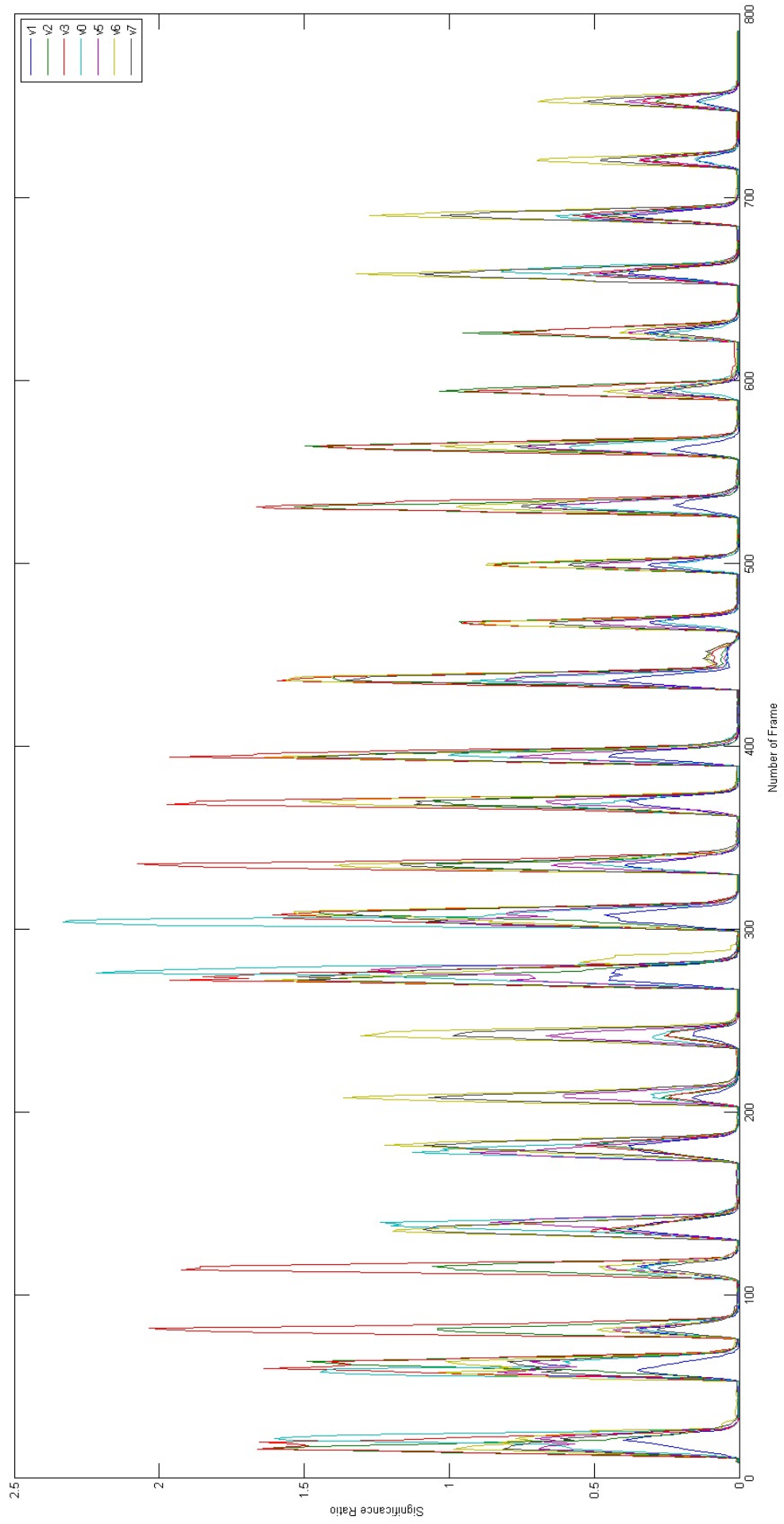


Figure 7.7: Segmentation through Inc-KSFA for different view perspectives, v1, v2, v3, v4, v5, v6, v7 represents different viewpoints while v0 represents the self-perspective.

which the action is observed.

To compare the performance of the proposed algorithm, a manual segmentation was performed based on the acquired image sequences. For manual segmentation, the frames are selected where there is a change in actions. In the manual examination, the position of segment between motion primitives was determined and each motion primitive was labelled manually. Figure 7.8 represents the comparison between the manual segmentation based on frames of images captured and proposed algorithm. For manual segmentation, the number of frames is calculated for which there is a change in action. The average segmentation ratio is computed for each action performed multiple times based on different repeating intervals between the motion primitive sequence. The results are summarized in Table 7.2. The segmentation accuracy is calculated between the boundaries (start and end) of the actions determined by Inc-KSFA and manual segmentation. In addition, to compare the performance of the proposed algorithm, segmentation is performed based on the change in recorded joint angle values.

Table 7.2: Segmentation accuracy of different types of actions performed

Label	Segmentation Accuracy [%]		Label	Segmentation Accuracy [%]	
	Start of Action	End of Action		Start of Action	End of Action
RAR180	99.199	98.281	RBAF	99.814	99.829
RAL180	99.316	97.642	LBAF	99.791	99.363
LAR180	99.419	98.835	RLAF90	99.874	99.051
LAL180	89.611	97.721	LLAF90	89.909	99.263
BAR180	99.601	88.872	RRAF	99.883	99.524
BAL180	99.633	98.961	LRAF	99.832	99.437
LAR90	99.623	98.843	RRAF90	99.886	99.739
LAL90	99.376	99.125	LRAF90	99.891	89.444
RAR90	99.688	96.341	RLAF	99.892	99.841
RAL90	99.809	99.918	LLAF	99.924	99.479
BAR90	99.765	99.496	RBAF90	99.995	99.601
BAL90	99.791	99.576	LBAF90	99.995	99.476

As can be seen from the results presented in Table 7.2, Figure 7.8 and Figure 7.9, the

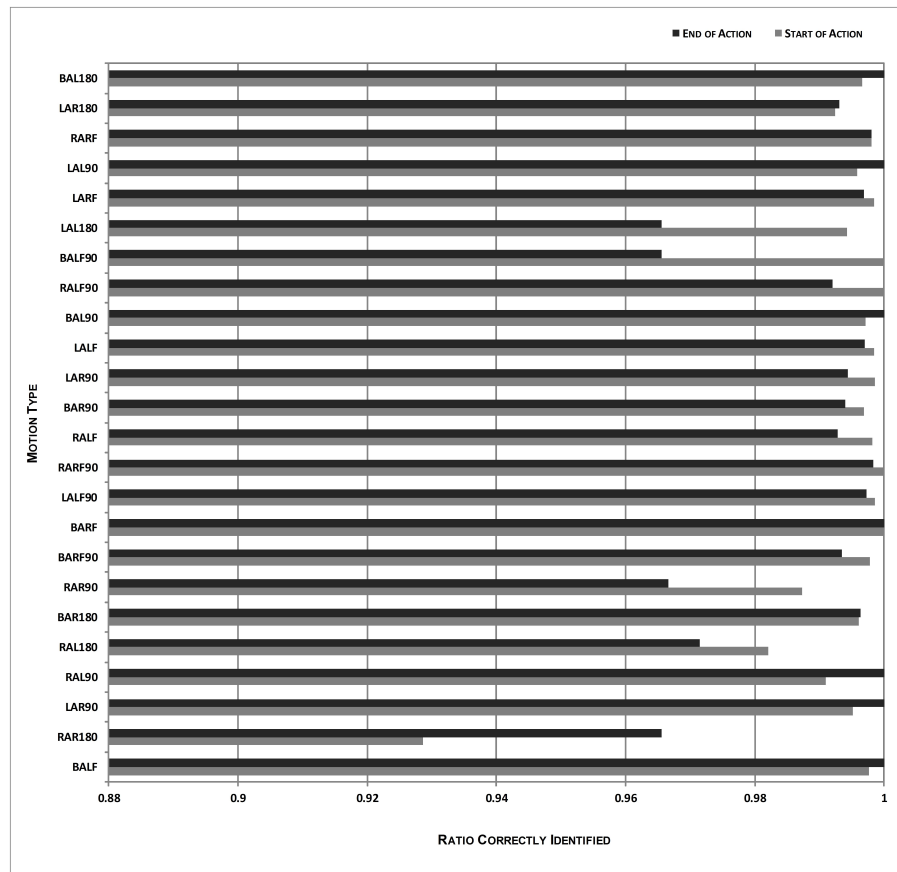


Figure 7.8: Accuracy of segmentation results between manual segmentation vs. Incremental Kernel SFA segmentation.

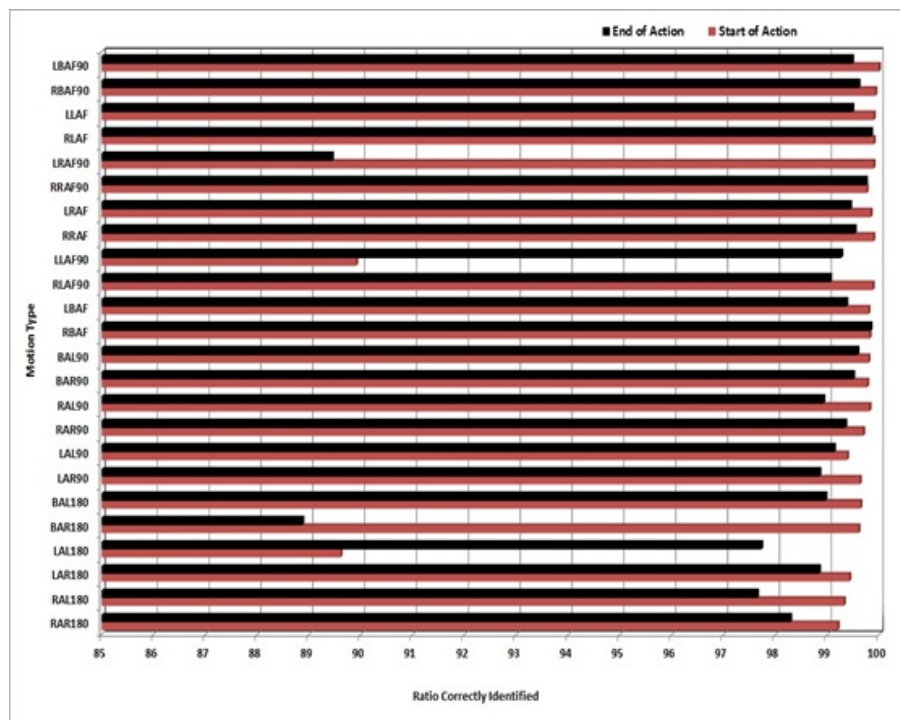


Figure 7.9: Accuracy of segmentation results between manual segmentation vs. Incremental Kernel SFA segmentation.

segmentation of the actions is performed with greater accuracy even at the critical points where the actions change from one motion primitive to another. In contrast, some motion primitives seem to be overlapping in their representation as they are often confused with each other. For example, at the beginning of recognition the RAR180 is confused with RRAF since the initial position of the joints is almost similar, however, they differ mostly at the end of motion primitive, as the recognition progresses with more images. Since the demonstration is a time-varying (spatio-temporal) representation, the robotic experiments revealed that the recognition or recall is based on retaining the entire sequence of representation units along the trajectory.

7.3 Incremental Learning

The continuous time series data composed of the upper part of the robot and joint angle values (motion elements) are used as input to the learning algorithm. The joint angle values are clustered based on the start and end of an action obtained from the Incremental Kernel SFA. The data were fed incrementally to the algorithm, simulating on-line acquisition, demonstrating the suitability of the proposed method for online learning. A Hidden Markov Model is used to abstract the observation sequences.

Once the start of an action is detected, TGAR-HMM starts adding the joint angle values as motion primitives in the form of nodes linked by edges. The learning of that particular action is completed when the end of that action is detected. I used left-to-right HMM model structure for representing observed motion patterns to allow the data to flow in a sequential order in the forward direction of time. In left-to-right HMM the self-transition loop is also allowed.

Initially, the topological map is empty, as no motion elements are processed at initialization. Each time a new motion element is observed by the learning algorithm, a corresponding node is added to the topological map. Each node representing the motion

element is labelled based on the labels acquired during the motion primitive segmentation. This indicates that the particular segment of motion has been learned as the motion primitive consistent with the added node. After learning, the specific episode of action is clustered according to its label (Figure 7.10). Thus, for each cluster, the observed action is learned by the observer in an incremental and online manner.

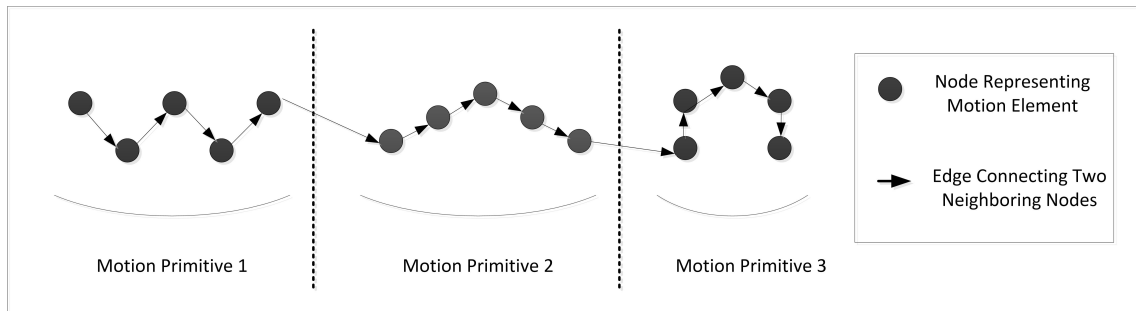


Figure 7.10: Overview of incremental learning algorithm. The circles represent the nodes encoding motion elements (joint angles) while the arrow represents the edges connecting these nodes. The "motion primitive" represents the labelled motion.

A motion primitive transition model is built incrementally by monitoring for instance when a sequence of two motion primitives is recognized by the algorithm. Each time a recognized motion primitive transition is detected, the corresponding edge is incremented. In this way, the robot incrementally learns how motion primitives may be combined during behavior execution.

As discussed earlier that the performance of TGARM greatly depends on the selection of values for the vigilance parameter and initial covariance matrix. For the vigilance parameter, the value is chosen to be $\rho = 0.85$, for fast learning and utilizing all the labelled nodes. The reason for selecting a value for the vigilance parameter is to generate the motion pattern as close as possible to the original pattern. This results in selection of optimal number of states or nodes during learning. Similarly, the initial covariance matrix determines the isotropic spread in feature space of a new node distribution. For large values of γ , the learning will be slow with fewer nodes, while smaller values of γ , the training will be faster with large number of nodes. The initial covariance matrix is

selected in an ad-hoc fashion by trial and error choosing the optimal value for the parameter. The experiments were performed for different values of the covariance matrix and then selecting the value which efficiently generalizes the observed patterns. These values are selected randomly from 0 to 10. The structure of covariance matrix is chosen such that diagonal elements are 0.3 while the remaining zero.

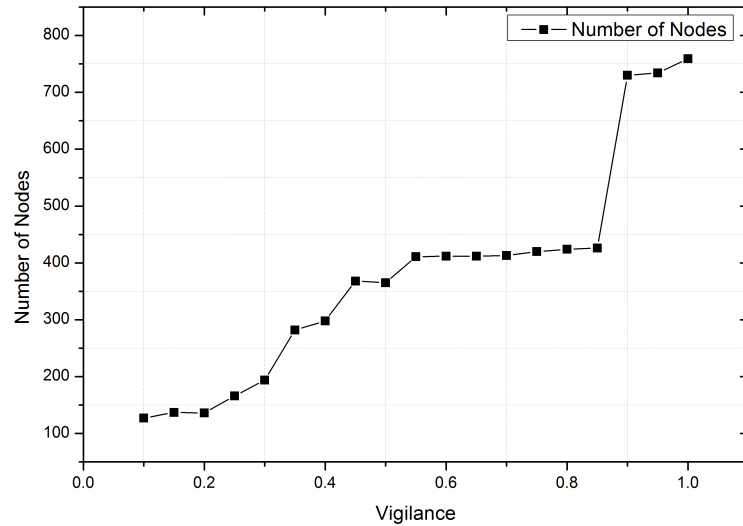


Figure 7.11: Effect of different values of vigilance parameter on the number of nodes.

7.4 Quality Measures for TGAR-HMM

7.4.1 Mean Square Error (MSE)

I used mean square error (MSE) or quantization error (QE) to estimate the difference between the learned behaviour and demonstrated behaviour. The quantization error is calculated by determining the mean distance of the sample vectors to the nodes created by the learning algorithm. For any data sample, the Quantization Error can be minimized by merely increasing the number of nodes in the topological map. This result in the data samples distributed more sparsely on the map. In case of TGAR-HMM the quantization error is affected by the selection of vigilance parameter value. Selecting the optimal value

of the vigilance parameter during learning process such that the QE is lowered.

$$QE = \frac{1}{N} \sum_{i=1}^N |O_t - y_{O_t}| \quad (7.1)$$

where O_t represents the input data sample and y_{O_t} is the node in the topological map.

N is the total number of input patterns provided to the TGAR-HMM during learning.

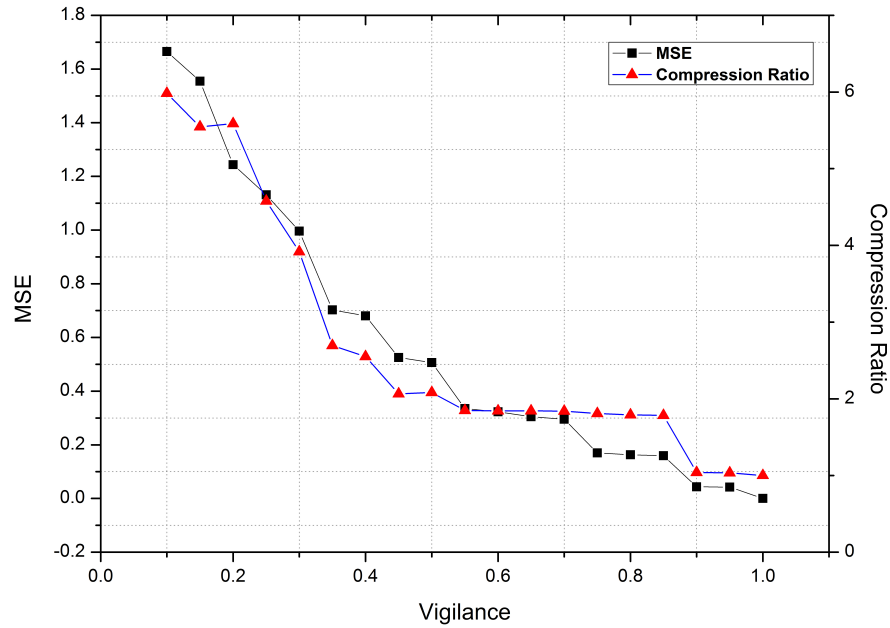


Figure 7.12: Plot for compression ratio and average mean square error for different values of vigilance parameter.

7.4.2 Compression Ratio (CR)

Compression ratio is determined by dividing the number of data samples in an action pattern and the number of nodes generated by the learning algorithm. For better encoding of the input patterns, the value of compression ratio must be minimized. In case of TGAR-HMM this ratio is controlled by the selection of vigilance parameter

$$CompressionRatio = \frac{\#InputPatterns}{\#Nodes} \quad (7.2)$$

Figure 7.12 shows the effect of selecting different values of the vigilance parameter on the compression rate and generalization error. As the value of vigilance parameter is

increased, the mean square error among the on observed and generalized values decreases by adding more number of nodes to the network. For higher values of vigilance parameter, the value of the compression ratio is decreased, resulting in encoding motion patterns as close as possible to the observed motion. Table 7.3 states the vigilance parameter values computed for different types of actions performed during the experiment.

Table 7.3: Evaluation criteria

Action Label	QE	CR	Action Label	QE	CR
RAR180	0.016334	1.34	RBAF	0.004629	1.033
RAL180	0.044525	1.33	LBAF	0.013058	1.333
LAR180	0.041529	1.068	RLAF90	0.056467	1.107
LAL180	0.018065	1.484	LLAF90	0.02595	1.151
BAR180	0.07784	1.142	RRAF	0.057632	1.107
BAL180	0.102003	1.03	LRAF	0.044525	1.515
LAR90	0.056403	1.318	RRAF90	0.056467	1.107
LAL90	0.058976	1.277	LRAF90	0.066709	1.151
RAR90	0.056403	1.107	RLAF	0.056467	1.107
RAL90	0.061566	1.192	LLAF	0.044525	1.151
BAR90	0.052058	1.068	RBAF90	0.007921	1.107
BAL90	0.087067	1.222	LBAF90	0.035384	1.181

Table 7.3 shows the quantization error (QE) and compression ratio (CR), respectively, for the values of the vigilance parameter for different action patterns. These results show that for the computed values of vigilance parameter, the quantization error is reduced. Moreover, for these vigilance parameter values, the compression ratio is also controlled by adding the optimal number of nodes.

I evaluate the performance of the system using error between the demonstrated and generalized motion to determine the appropriate adapting learned motion. The mean error is used as a metric to evaluate the sustainability of the generalized motion with respect to the demonstrated motion. This error metric provides a measure for the evaluation of generalization capability of the proposed learning model. Figure 7.14 shows generalization results from the action of raising both arms 90deg (RBA90), a combined action consisting of raise both arms 90deg, and lowering both arms 90deg (RBA90-LBA90), raise and

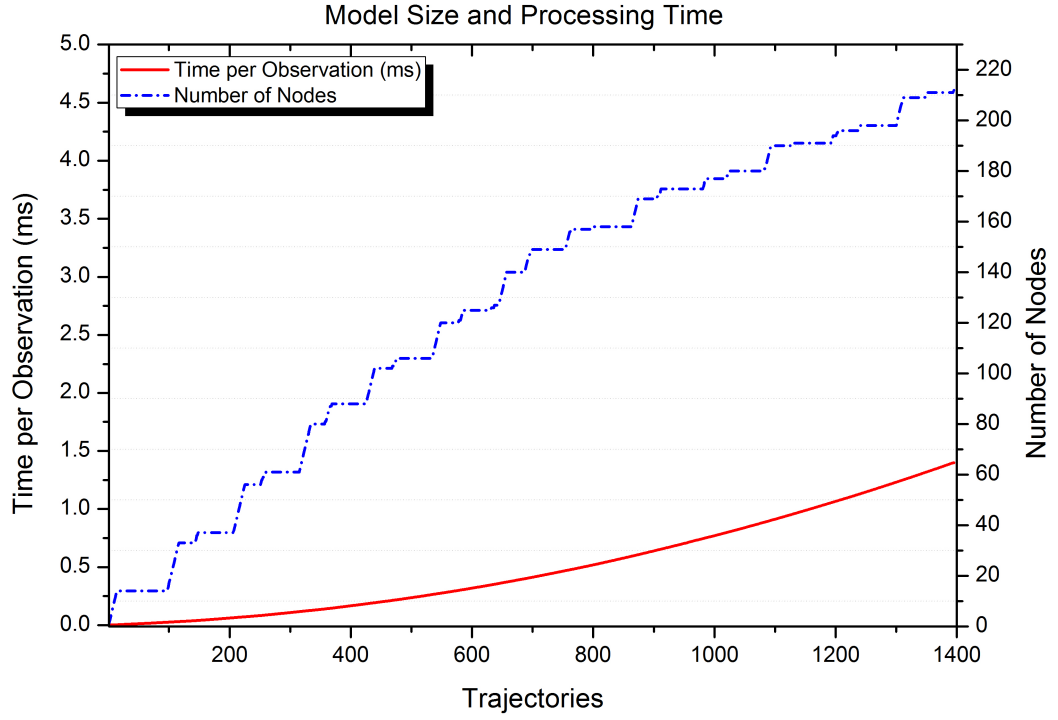


Figure 7.13: Computation times.

lowering both arms from by 90deg (RBAF90-LBAF90) and raising and lowering both arms front (RBAF-LBAF).

The structure of the transition matrix is the fundamental complexity factor for inference on HMMs. Therefore, we measure the size of the model by the number of nodes in the transition graph. Figure 7.13 plots the processing time taken by learning algorithm with respect to the number of trajectories. The model size is represented as the number of nodes in the TGAR-HMM structure is also given as a reference. As may be anticipated, the learning time appears to be linearly dependent on the size of model. An interesting observation is that the time per observation is lower than 1ms. Thus, algorithm is well adapted for on-line applications in the environment where it is likely to observe fewer trajectories per second.

7.5 Associative Learning and Recall

For a completely accurate evaluation of motion primitive recognition in the proposed system, the memorized commands are required to perfectly match those that were actually

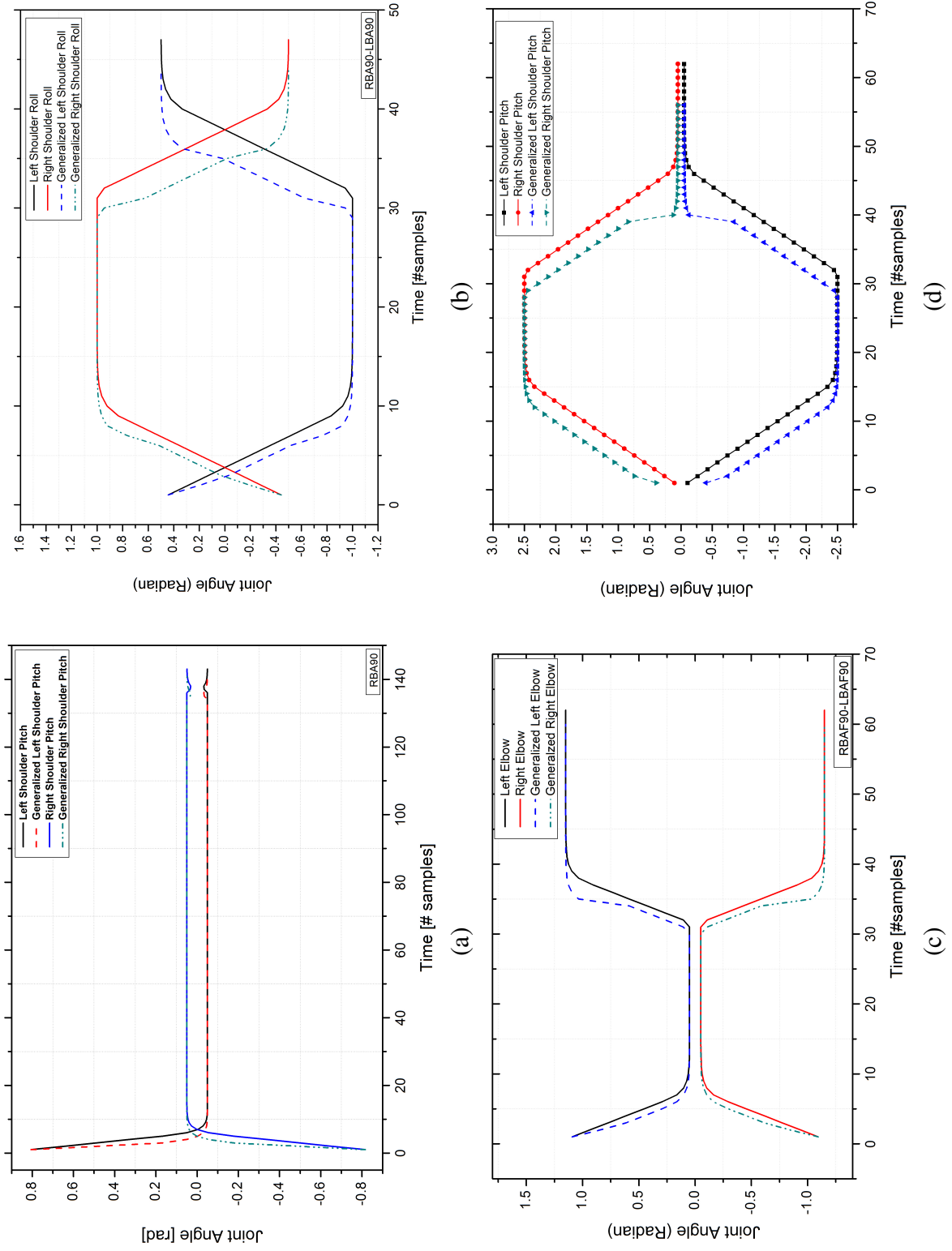


Figure 7.14: Plot of original and learned motion patterns for actions: (a) RBA90, (b) RBA90-LBAF90, (c) RBAF90-LBAF90, (d) RBAF-LBAF.

executed by the demonstrator, so that each motion primitive in the system recognizes can then be labelled. During recall process, an image from the test set was presented and processed as in Section 6.2. With the resulting set of joint-angles, the robot arm is able to perform the demonstrated action.

As mentioned earlier, the proposed mirror neuron model for the robot first develops an association amongst the robot's actions and corresponding visual representations from the self-observed perspective. First, the experiments with the self-observing perspective are performed and the association is developed from that perspective symbolizing the PF pathway between STS and F5. The robot associates its own movements with their visual appearance on the basis of TGARM. Later, the model is trained from different perspectives and the robot performs association with the behavioural actions observed from other different perspectives. For experimentation scenario, the robot initially executes the actions while observing the self-perspective by visualizing its body in the mirror. Directly after this, assuming that the motor patterns are still active, the robot comprehends the same action from a different perspective.

Table 7.4: Result of Associative Recall

	Number of Experiments	Recall Rate [%]
Self-Perspective	5	100
View-invariant Perspective	5	100

From these experiments I conclude that any visual representation of a specific movement will trigger an appropriate motor command of that particular action, depicting the activity of mirror neuron. The results of the recall rate of the associative memory are summarized in Table 7.4. The activation of motor information utilizing different perspective visual input can be used to alleviate the process of devising invariant representation of the actions in STSa.

Noise tolerance is a significant function in associative memory. I test the noise toler-

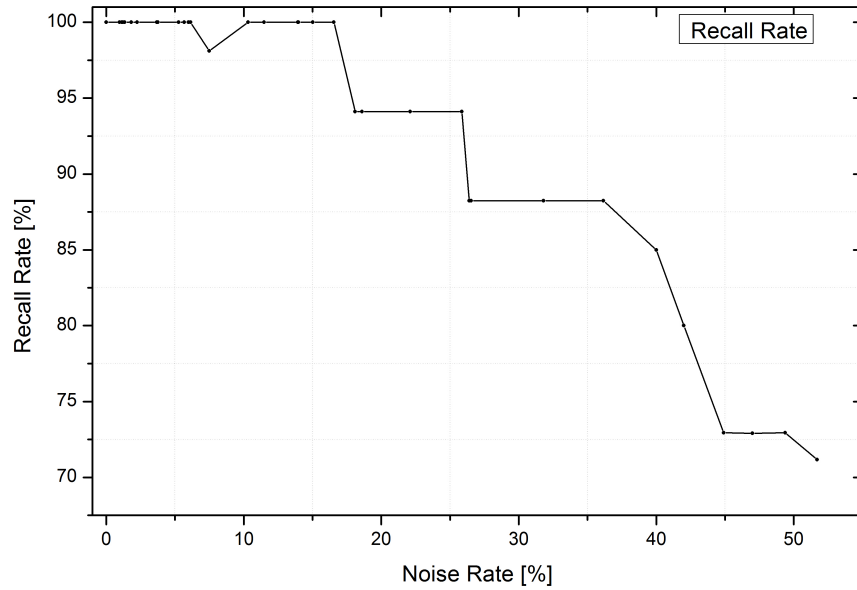


Figure 7.15: Effect of noise on the recall rate.

ance by adding the noises on input images sequences randomly. TGAR-AM shows quite high recall rate even if input data contains high noise rate. For example, for the noise rate of 50% the recall rate is around 73%. The recall rate of the demonstrated action is presented in Figure 7.15.

7.6 From Primitive Motion to Complex Behaviors

I now try to investigate if new actions can be modelled using learned motion primitives through visuomotor association. I believe that the extracted physical features are also effective to combine one motion pattern with another motion pattern. Combining motion patterns mean that a specified motion pattern is performed simultaneously with another motion pattern. Every time a known motion primitive is observed, the robot incrementally learns and recalls how motion primitives may be combined throughout behavior execution.

During experimentation, new complex behaviours are produced by combining successions of motion primitives. For example, the punch action generated by the combination of two already learned motion primitives labelled RLAF90 and RLA (Figure 7.16).

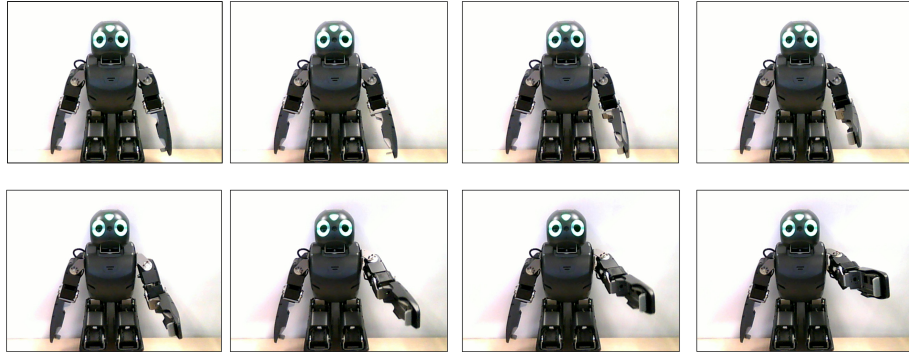


Figure 7.16: "Punch" action

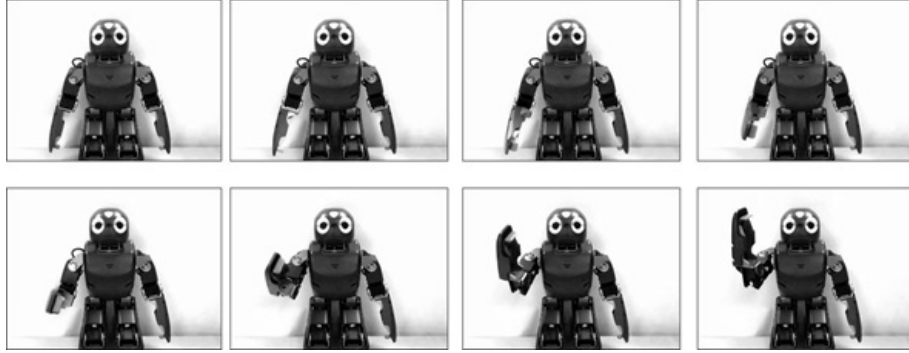


Figure 7.17: "Hi" action

Similarly, the composite action of 'Hi' is generated in the same manner (Figure 7.17). Initially, the learning process begins with only describing basic motion primitives. Later, behaviours that are more complex are produced by combining two or more motion primitives. Behaviours are generated by forming an abstraction above the motion primitive level. Once the learner can recognize the observed behavior, it can recall the appropriate motion primitives from the associative memory to generate the complex behaviours.

In generating and recognizing complex behavior phase, already learned motion primitives are utilized as states of TGAR-HMM. During the generation of complex behaviors, active behavior is accountable to generate the suitable motor commands. Category estimation phase reckons the labelled sensory data to extract the suitable motion primitives of new observed complex behavior in order to determine observation sequence from current observation to goal observation. These motion primitives are already learned during motor babbling phase.

Complex behaviors generation stage is analogous to generating simple behavior. Ob-

ervation sequence is rendered by estimating the most likely state sequence in the highest probability for each motion primitive estimated using the categories to perform the observed behaviour. Afterwards, the generation of motor commands begins from the first behavior in the observation sequence. The corresponding intermediate motion primitive in the observation sequence is considered as the low level behavior as goal observation. When execution of a particular motion primitive is finished, the system moves on to the next motion primitive in the sequence. This operation continued until all motion primitives in the observed sequence are executed.

CHAPTER 8 – CONCLUSION AND FUTURE DIRECTIONS

I presented a developmental framework for humanoid robot demonstrating that it is able to learn by imitation through self-exploration. The proposed model is based on the assumption that the humanoid robot does not have a priori knowledge about itself. It must therefore build a model of the self. The robot first learns about its own body gathering all information by self-exploration through body babbling. I looked into the proposed system's ability to imitate from a cognitive science point of view instead of engineering perspective in order to acquire knowledge of the possibility for simple imitation capabilities to be associated with self-experience given the simple (innate) capacities of the system (the newborn). This path allows the robot to acquire increasingly more sophisticated skills.

The contribution of this thesis is summarized as follows:

- Body babbling or self-exploration for the acquisition of sensory associations, enabling the humanoid robot to develop early imitative abilities. The proposed mirror experiment demonstrates the feasibility of learning motor control through self-exploration.
- I developed an algorithm for online temporal segmentation through Incremental Kernel SFA to define the boundaries of motion primitives (start and end of an action). This method is based on the visual data acquired from the robot's camera. The proposed method is able to segment the actions with an overall average accuracy of 98.896% and 98.235% in determining the start and end of actions, respectively. These primitive segments are further utilized to generate complex behaviour by the combination of two or more motion primitives learned during self-exploration.

- Incremental and on-line learning algorithm for continuous flow of motion patterns based on novel Topological Gaussian Adaptive Resonance Hidden Markov Model. Learning new sequences of motion to create a stable topological structure of the input trajectory by adjusting the structure of probabilistic model (i.e. estimating the number of states). The algorithm is capable of learning in real-time without defining the structure of the model a priori.

The aim of the proposed learning algorithm is not to exactly trace back the original trajectory sequence as this will result in large number of nodes or HMM states. This results in selection of optimal number of states or nodes from the measured data. This selection is controlled by the vigilance parameter. Although the selection of vigilance is done manually using trial and error method, but the current experiments show that once the suitable value of vigilance parameter is selected from a particular data set, it can be efficiently applied to different kinds of motion sequences. However, an improved method for selection or adaptively modifying the value of vigilance parameter will efficiently provide a better generalization performance.

- Linking the observed self-exploratory action with its own motor commands to understand the perceived actions emphasizing the actions performed by the demonstrator rather than the view-point from it is observed. The proposed TGAR-AM algorithm is able to incrementally develop the association between the different types of input data without any predefined conditions. When forming the association between self-observing perspective and motor representation, the associative memory has no difficulties to converge to 100% success. Even with a noise rate of more than 50%, the system has a recall rate of about 70%.

The objective of the results reported was to test whether the ability to imitate could emerge from learning of sensori-motor associations resulting from self-observation. The

results obtained can be considered as the developmental steps towards allowing robots to systematically learn how to integrate perception and action through self-experiences much like a human being does, to generate adaptive behaviours efficiently and flexibly. In the initial phase, the proposed system develops perception ability of the self body from low-level visuomotor signals and proceeds to learn primitive actions in the next phase. Before learning, the motion primitives are segmented autonomously by defining the start and end of particular actions. In the later phase, the segmented motion primitives are learned using an approach for continuous learning and allowable motion primitive sequencing through observation of a demonstrator. As each motion primitive is learned, it is also organized in a topological map, which is incrementally updated to learn the relationship and sequencing of the motion primitives. The algorithm is capable of learning in real-time, during observation of the demonstrator's motions. The development of a topological structure of the learned motion primitives allows for easier retrieval, and the automatic generation. A visuomotor association is developed between the self-observed images and segmented motion primitives. In the final phase, the recognition of complex behaviours is performed by combining already learned primitive actions.

The main result from the robotic implementation is that this associative network trained by self-observation is capable of action contagion. It exhibits one-shot imitation i.e., without training the motor code corresponding to a new posture presented can be inferred and hence executed. In accordance with the theoretical framework which inspired this experiment, I illustrated that observation of the actions of the self can be used to associate synchronous visual and motor aspects of an action by application of associative memory. The stored visuomotor patterns can be seen as internal models of actions.

8.1 Future Work

Future work will focus on implementing full body motion on the humanoid robot, as well as motions involving interaction with the human environment. In addition, techniques for generating the motions with a desired goal or execution criteria based on the motion primitive will be developed, as well as the use of the motion primitive for human activity detection and motion prediction. Further improvements to the clustering part of the algorithm will be considered, such as automatic labelling of learned and segmented motion patterns. This will help in efficiently arranging the learned data in the memory by removing the redundant information. The system can only perform the behavioural gestures. In future work, we are planning to focus on the issues of view-invariant imitation for complex actions or tasks involving different types of objects.

A key piece of our learning system is the selection of vigilance parameter which effects the performance of the system. Although the selection of vigilance is done manually using trial and error method, but the current experiments shows that once the suitable value of vigilance parameter is selected for a articular dataset, it can be efficiently applied to different kinds of motion sequences. However, an improved method for selection or adaptively modifying the value of vigilance parameter will efficiently provide a better generalization performance.

APPENDIX A – PUBLICATIONS

A.1 Journal Papers

1. Dawood, F., & Loo, C. K. (2015). Incremental Episodic Segmentation and Imitative Learning of Humanoid Robot through Self-Exploration. *Neurocomputing*. [Accepted]
2. Dawood, F., & Loo, C. K. (2015). Robot Behaviour Learning using Topological Gaussian Adaptive Resonance Hidden Markov Model. *Neural Computing and Applications*. [Accepted]

A.2 Conference Papers

1. Dawood, F., Loo, C. K., & Chin, W. H. (2013). Incremental on-line learning of human motion using Gaussian adaptive resonance hidden Markov model. *In Proceedings of Neural Networks (IJCNN), The 2013 International Joint Conference on*, Dallas, USA.
2. Dawood, F., Loo, C. K. (2014). Autonomous Motion Primitive Segmentation of Actions for Incremental Imitative Learning of Humanoid. *In Proceedings of IEEE Symposium Series on Computational Intelligence (IEEE SSCI 2014)*, Florida, USA.
3. Dawood, F., Loo, C. K. (2014). Humanoid Behaviour Learning through Visuomotor Association by Self-Imitation. *In Proceedings of Joint 7th International Conference on Soft Computing and Intelligent Systems and 15th International Symposium on Advanced Intelligent Systems (SCIS & ISIS 2014)*, Kitakyushu, Japan.

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